Rural Poverty

by

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Abstract

Despite strong growth during the 1990s economic expansion being accompanied by significant reductions in measures of U.S. poverty, high poverty persisted in remote rural areas. Therefore, this study uses a novel geographical information system database of county-urban proximity measures to examine the nexus between poverty in rural U.S. counties and their remoteness, particularly in regard to their geographical proximity to larger urban centers. We find ceteris paribus increases in poverty rates for greater rural distances from successively higher-tiered metropolitan areas. We explain this outcome as arising from the attenuation of urban agglomeration effects with greater distance and incomplete labor supply adjustments in remote rural areas. Thus, our results suggest future poverty reduction as the rural population increasingly concentrates near urban areas. Moreover, our results suggest that although they are at a disadvantage in terms of higher poverty rates, remote rural areas also may particularly benefit from place-based economic development policies.

JEL: R12, I32, R23

1. Introduction

Strong U.S. macroeconomic performance during the 1990s was accompanied by a reduction in the overall person poverty rate to 11.3 percent, the lowest since 1974 (U.S. Census Bureau, 2006).[1] The apparent strong link between economic growth and poverty reduction was notable given its near absence during the 1980s (Freeman, 2001). Yet, poverty remains much higher in nonmetropolitan counties, particularly for those far removed from metropolitan areas (Partridge and Rickman, 2006, Ch. 2).

An extensive literature exists on whether there is a rural poverty effect. In their survey, Weber et al. (2005) contend that not only does nonmetropolitan America have higher poverty in general, poverty is higher and more persistent in remote counties.[2] But is poverty higher in these areas because of their remoteness, or because of other factors such as natural amenities or the demographic composition of the local population? Despite the emphasis on distance in New Economic Geography models and regional economics in general, to the best of our knowledge there have not been any studies that have empirically assessed the nexus between poverty in rural areas and their geographic proximity in the urban hierarchy.

Distance can affect poverty through influencing both rural labor demand and supply. Shorter distances between firms yield many economic advantages for metropolitan areas, leading to agglomeration of economic activity (for a survey see Rosenthal and Strange, 2001). Yet, agglomeration benefits such as higher wages attenuate with distance from the core area (Hanson, 1997). Empirically, distance appears to be a key factor underlying employment and population growth in nonmetropolitan counties. Those adjacent to metropolitan areas grew fastest during the 1990s (USDA, 2006), and *ceteris paribus*, the greater the distance from larger urban core areas, the lower was nonmetropolitan growth during this period (Partridge et al., 2006a; 2006b).[3]

Despite weaker labor demand in remote rural areas, offsetting out-migration of labor from rural areas could raise rural wages and reduce rural poverty. These equilibrium adjustments would make long-run poverty more a function of household characteristics (Ravallion and Wodon, 1999). Yet distance also

[1] In analyses of state poverty rate trends, Gundersen and Ziliak (2004) and Partridge and Rickman (2006, Ch. 4) concluded that it was strong economic performance that primarily reduced poverty in the 1990s, not welfare reform.

[2] Since official poverty rates are not adjusted for regional cost of living differentials, there has been considerable speculation on whether lower prices in nonmetropolitan areas, particularly for housing, equalize real poverty rates across nonmetropolitan and metropolitan areas. Nevertheless, the U.S. General Accounting Office (1995) has concluded there is insufficient official data to geographically adjust poverty rates for price. Moreover, costs of food and other items such as transportation could be higher in the most remote rural areas because of delivery costs and distance, offsetting housing cost advantages (Nord and Leibtag, 2005).

[3] Desmet and Fafchamps (2005) also report increased concentration of U.S. employment from 1972 to 2000.

can limit labor mobility by raising the costs of commuting and migration, which produces higher poverty in remote areas. Distance can reduce labor mobility because of associated information and relocation costs, both pecuniary and non-pecuniary. Furthermore, if these costs lead to longer residence durations in rural areas, they can dynamically increase relocation costs through increasing ties to the area, creating inertia effects (Molho, 1995). The lower long-term labor supply elasticity due to remoteness suggests that distance-based limitations on rural household access to good paying jobs can create a rural spatial-skills mismatch that is akin to inner-city spatial mismatch outcomes that predominate the urban literature (Blumenberg and Shiki, 2004). Nevertheless, despite nonmetropolitan poverty rates that greatly exceed metropolitan rates, there has been remarkably little examination of spatial location and rural poverty.

Therefore, this paper empirically examines the relationship between nonmetropolitan poverty rates and distance from metropolitan areas. A key contribution of our study is the construction of a large geographical information system database of urban proximity measures for every U.S. county. This allows us to estimate the poverty effects of nonmetropolitan county distances from successively higher-tiered metropolitan areas, which to our knowledge, has never been explored in past research. If economic activity continues to concentrate in and near the larger urban areas, then a county's labor demand growth should be inversely related to its distance from successively higher-level urban tiers. And to the extent nonmetropolitan labor supply responses are not offsetting, poverty rates would be expected, *ceteris paribus*, to be positively associated with increased distance from each higher-ordered urban tier.

The next section more formally models the link between nonmetropolitan poverty and distance from metropolitan agglomerations. The empirical model and implementation follow in Section 3. Section 4 presents the results. We find that poverty increases with greater distance from each successive tier of metropolitan area, even when accounting for a host of county characteristics such as the area's amenity attractiveness and the demographic composition of the local population. The final section provides a summary and offers policy recommendations. Possible policies include "urbanization trickle down," where the prospects of the rural poor are lifted by better access to urban jobs in conjunction with urban growth that spreads into the countryside. Yet the same accessibility factors that give rise to the distance effect on poverty imply that employment growth has greater antipoverty effects in more remote areas. We thus argue for the need for place-based antipoverty policies and offer some suggestions in their design.

2. Poverty and Distance from Metropolitan Areas

Area aggregate poverty rates derive from both economic and non-economic factors. Among economic factors, the poverty rate in an area (pov) has been significantly linked to labor income, which is given by the area's employment rate among working age adults (er) and the associated wage rate (wr).[4] Thus, we express the area poverty rate as:

(1) $pov = f^{p}(er{*}wr,\bullet)$,

where • denotes all other factors, which include non-economic factors such as the area's demographic characteristics. The employment and wage rates can be thought of as full-time employment equivalents. The aggregate wage rate also depends on the occupational and sectoral composition of the area.

The employment and wage rates are reduced-form outcomes from the interaction of labor demand (l^{d}) and labor supply (l^{s}) (Partridge and Rickman, 2003):

(2) $er = f^{er}(l^{d}, l^{s})$

(3) $wr = f^{wr}(l^{d}, l^{s})$,

where the labor market outcomes for the lesser skilled and educated may be paramount in the determination of the poverty rate.

Labor demand derives from location optimizing decisions by firms, which depend on a myriad of revenue and cost considerations related to distance. If metropolitan areas are associated with agglomeration economies, greater distance from metropolitan areas may negatively affect profits and labor demand in nonmetropolitan areas, depressing their employment and wage rates, and increasing their poverty rates. Various theories have emerged to explain agglomeration of economic activity.

From New Economic Geography, for example, close proximity of urban firms to their intermediate input suppliers and customers lowers their transportation costs (Venables, 1996), causing firms to agglomerate. Costly transportation then disadvantages areas more distant from metropolitan areas. Transactions costs such as costly information about demand conditions and trustworthy suppliers also increase with remoteness, inhibiting trade (Hanson, 1998). Other sources of agglomeration can occur through knowledge spillovers between firms and labor-market pooling (Rosenthal and Strange, 2001). Likewise, greater distance from metropolitan areas also may limit work-commuting opportunities in

[4]For a review of the literature on the link between regional labor market outcomes and poverty, see Partridge and Rickman (2006, Chapter 4).

nonmetropolitan areas (Partridge et al., forthcoming) and access to credit (Bigman and Fofack, 2000). Yet, forces limiting agglomeration include increased price competition associated with close proximity of economic activity (Krugman, 1993), and congestion costs, such as higher crime, pollution, and land prices (Glaeser, 1997).

Even if distance creates inequality in labor demand, household mobility with fully elastic labor supply would arbitrage away distance-based differentials in labor earnings (assuming homogeneous household preferences regarding residential location). Out-migration of non-employed (or under employed) nonmetropolitan households would increase employment and wage rates among those remaining, reducing poverty. However, distance may affect the extent labor supply responds to metropolitan-nonmetropolitan labor demand differentials.

Information costs regarding job opportunities increase with distance (Lucas, 2001). Rural households then may only search in labor markets with similarities to the origin market (Gibbs, 1994), which likely precludes them from searching in urban areas. Besides similarity in labor markets, poor rural households also may only move to other poor rural areas because of cultural similarities, the availability of support networks, and low housing costs (Nord, 1998). Molho (1995) argues that the lower out-migration that arises from greater remoteness leads to longer residence durations in rural areas, which then creates cumulative inertia effects such as the building of more friendships, further limiting out-migration. Henderson and Wang (2005) formally model differential wealth holdings in agriculture and differential skill endowments as limiting rural out migration. If high-skilled labor is complementary with low-skilled labor in production, out-migration of high-skilled labor further depresses low-skilled wage rates, particularly if low-skilled laborers do not obtain the necessary training and education to replace those departing (Lucas, 2001).

With limited commuting and migration flows, long-run labor supply is more inelastic in remote areas. Thus, remoteness makes poor rural residents more dependent on local jobs. In terms of labor supply responses, the upside from lower in-commuting and in-migration is that job growth in remote rural areas more likely “trickles down” to the original local residents (Bartik, 1993). Of course, the downside is job losses in remote areas would raise poverty even more under these circumstances, such as when resource-based sectors face persistent decline.

Therefore, we express both nonmetropolitan labor demand and labor supply as dependent on an area's distance from metropolitan areas:

(4) $l^d=f^{dd}(dist, \bullet)$

(5) $l^s = f^{ds}(dist, \bullet)$.

Hence, through the effects of distance on labor market outcomes, poverty rates in nonmetropolitan areas are indirectly related to their distances from metropolitan areas:

(6) $pov= f^{pov}(dist, \bullet)$.

In equation (6), *dist* positively affects nonmetro poverty because (net) agglomeration economies attenuate with distance from metropolitan areas, and labor supply responses by poor nonmetropolitan households are incomplete. The result is a form of spatial mismatch in nonmetropolitan areas (Blumenberg and Shiki, 2004) akin to urban spatial mismatch, in which there are problems of geographic accessibility to best-matching jobs for low-income households. The causal mechanisms also have some commonality with those underlying rural poverty traps in developing countries (e.g., Lucas, 2001).

3. Empirical Implementation

The primary empirical innovations in our specification are accounting for nonmetropolitan location within the urban hierarchy and other rural-urban interactions that can affect rural poverty outcomes. Nevertheless, our base (full) formulation is consistent with prior spatial studies of overall poverty rates in terms of specification and control variables (Madden, 1996; Levernier et al., 2000; Gundersen and Ziliak, 2004; Partridge and Rickman, 2005). Although parsimonious models are considered, the fully specified model accounts for labor market factors that affect wages and labor-force participation, as well as the region's demographic characteristics. A partial (disequilibrium) adjustment formulation allows for the possibility that poverty responds sluggishly to changes in socioeconomic conditions, making current poverty related to past poverty.

Each county has its own expected (equilibrium) poverty rate given its characteristics. Changes over time in the underlying attributes change the expected (equilibrium) poverty rate. Economic shocks also shift the expected poverty rate. It may take time for the labor market to respond and for the actual poverty rate to move to the expected rate. Given the prevalence of economic (and demographic) shocks, it is unlikely that a region's actual poverty rate equals its expected rate. Thus, the current poverty rate is a

function of initial characteristics that determine the expected poverty rate, current/recent economic conditions, and the lagged poverty rate to account for disequilibrium adjustment. A significant coefficient for the lagged poverty rate suggests a slow adjustment to socioeconomic shocks, making poverty rates autoregressive. An insignificant coefficient indicates a rapid adjustment. Accounting for the lagged poverty rate also helps control for any "fixed effects" that persistently lead to a high or low county poverty rate.

Table 1 lists the variables used in the empirical model. The dependent variable is the overall 1999 county person poverty rate.[5] Most of the causal variables are generally self-explanatory, in which most of our attention will be on the urban proximity and related urban spillover variables. Except for the job growth variables, the values of the base model's explanatory variables are measured around 1990 or before. We assume that initial conditions in the local region determine its long-run expected (equilibrium) poverty rate. A key empirical advantage of controlling for initial (pre-determined) conditions such as demographics is it should greatly mitigate any simultaneous causality with current poverty rates. In sensitivity analysis, we assess this assumption by considering parsimonious models and by using contemporaneous values of the explanatory variables measured around the year 2000. Forming our base model, the following empirical model is estimated for nonmetropolitan counties (county i in state s):

$$(7)\ POV_{is1999} = \alpha POV_{is1989} + \theta AVGNEIGBORPOV_{is1989} + \delta \mathbf{PROXIMITY}_{\mathbf{is}} + \boldsymbol{\varphi} \mathbf{ECON}_{\mathrm{is1990s}} + \boldsymbol{\beta} \mathbf{CTY_TYPE}_{\mathrm{is}} + \boldsymbol{\gamma} \mathbf{DEMOG}_{\mathrm{is1990}} + \sigma_{\mathrm{s}} + \varepsilon_{\mathrm{is1999}}.$$

For the explanatory factors, *AVGNEIGHBOR* is the average 1989 poverty rate in contiguous counties (includes all counties in its derivation including neighboring metropolitan and nonmetropolitan counties), which helps pick up spatial spillover/clustering effects.

Reflecting the key variables of interest, the **PROXIMITY** vector includes measures of the county's proximity within the urban hierarchy as well as urban spillovers. For this study, an urban center is defined as a metropolitan area (MA).[6] Thus, the first measure is distance to the nearest urban center of any size, which

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[5]Poverty rates are defined by the U.S. Census Bureau definition. Unless otherwise indicated, the variables are drawn from Census 1990 and Census 2000 SF3 files available online at www.census.gov at *American Fact Finder*. One exception is the distance variables, which are derived using geographical information systems.

[6]However, beginning with 2003, nonmetropolitan counties were classified as part of micropolitan areas by the U.S. Census Bureau if they had "cities" of 10,000-49,999 population or tight commuting linkages to the city. The remaining nonmetropolitan counties are classified as non-core-based statistical areas. We do not distinguish between them in our analysis.

is measured as the distance from the county's centroid to the centroid of the nearest MA.[7] This variable reflects a variety of access penalties. First, distance reflects the cost to access urban jobs (Henry et al., 1997, 2001; Partridge et al., forthcoming). For low-income workers (and other rural workers), urban areas likely have greater numbers of jobs that yield better employment matches and higher wages. Second, close access to urban centers improves the economic vitality of proximate rural communities. Local economic prospects are heightened because urban customers are nearby and closer access strengthens input-output linkages with the urban center (including lower transportation costs). Finally, closer proximity implies that there is better access to higher-ordered urban services and amenities for the rural community's businesses and households.

We include the incremental distances to more populous higher-tiered urban centers to reflect the additional net effect of "penalties" or "protection" from being more distant from cities further up the hierarchy. For example, greater remoteness from larger cities could inhibit rural growth due to less access to higher-order urban services and amenities. On the other hand, spatial competition from large urban centers may limit growth in nearby communities, which are referred to as agglomeration growth shadows in the New Economic Geography literature (Fujita et al., 1999).

To reflect these effects, we include the incremental distance in kilometers from the rural county to reach a MA with population of at least 250,000, which may be zero kms if the nearest MA is already over 250,000.[8] We also include the corresponding incremental distance to reach a metropolitan area of at least 500,000 and at least 1.5 million.[9] Reflecting agglomeration and congestion effects for both firms and households, the thresholds are consistent with those of Overman and Ioannides (2001). The largest category generally corresponds to national and top-tier regional centers, with the 500,000-1.5 million category reflecting sub-regional tiers. The smaller-size thresholds reflect different-size labor markets (for commuting) and varying access to personal and business services.

[7] The population-weighted county centroids are from the U.S. Census Bureau, which were also used to calculate the population-weighted centroids of multi-county MAs. The size categories of the MAs are determined by the MA's initial 1990 population.

[8] For example, if a rural county is 50kms from the nearest MA of (say) 100,000 population and 120kms to a MA of 300,000, the incremental distance to the nearest MA of at least 250,000 would be 70kms (120-50).

[9] Incremental distance is calculated as before. If the county is already nearest to a MA that is either larger than or equal to its own size classification, then the incremental value is zero. For example, if the county's nearest urban center of any size (or MA of any size) is already over 500,000, then the incremental values for the at least 250,000 and at least 500,000 categories are both equal to zero. To take another example, suppose rural county A is 30kms from its nearest MA, which has 100,000 residents, 80kms from its nearest MA >250,000 people (say 400,000 population), 200kms from a MA >500,000 (which happens to be 3 million). Then the incremental distances are 50kms to the nearest MA>250,000 (80-30), 120 incremental kms to the nearest MA>500,000 (200-80), and 0 incremental kms to a MA >1.5million (200-200).

Other variables in the **PROXIMITY** vector include population of the nearest metropolitan center, which captures additional agglomeration or dispersion of economic activity associated with marginal changes in its population. Although urbanization economies draw resources from rural areas into the urban core, rural areas closest to urban areas may fare better than the remote areas. For example, nearby rural firms may benefit from thicker labor pools and closer proximity to higher-order inputs and markets (Partridge et al., 2006a; 2006b). Congestion effects also may cause rural areas close to large urban centers to grow as economic activity disperses from the urban core.

The **ECON** vector contains measures of job growth and industry restructuring. First, we include measures of 1990-1995 and 1995-2000 county employment growth using place of work data from the U.S. Bureau of Economic Analysis.[10] Because 1995-2000 job growth may be endogenously determined with 1999 poverty rates (the dependent variable), we substitute the industry mix variable from shift-share analysis as an exogenous proxy for local labor demand shifts.[11] That is, if a rural county has a high intensity of relatively slow-growing agriculture and natural resource industries in the 1990s, then it would be expected to have fewer work opportunities and higher poverty rates. Because employment growth over the entire decade is considered, we assess the degree to which prolonged job growth is necessary to ensure that employers hire disadvantaged workers rather than other members of the labor force.

In sensitivity analysis, we also interact the distance from the nearest MA with a measure of the own county's 1995-2000 industry mix job growth to examine the hypothesis that a greater proportion of local job growth trickles down to disadvantaged original residents in more remote rural areas. Likewise, to examine the degree to which urban job growth "trickles out" to the rural poor, we also jointly include a measure of the MA's job growth and its interaction with distance to the MA. This somewhat disentangles the effect of commuting opportunities provided by urban areas from other urban proximity benefits.

Industry restructuring is measured as the share of employment that has shifted across sectors over the

[10]Theory does not provide guidance as to the timing of the linkage between job growth and poverty. Experimentation at the own-county level with various time periods revealed that five-year (e.g., 1995-2000) measures were superior to those from other periods, which were often highly insignificant. We use 10-year measures when considering growth in the nearest MA. See Partridge and Rickman (2006) for more details of how the employment data was gathered.

[11]Industry mix growth is a common exogenous measure of demand shifts. Industry mix employment growth is the sum of the county's initial industry employment shares multiplied by the corresponding national industry growth rates over the subsequent period. Because national industry growth should be exogenous to industry growth in a given county, it is routinely used as an instrument for local job growth and local demand shifts (e.g., Bartik, 1991; Blanchard and Katz, 1992).

recent period using a dissimilarity index. More restructuring is expected to increase poverty through job dislocation and problems associated with finding comparable new work. We also interact the restructuring variable with population to consider whether thicker labor markets are associated with better job matching following restructuring, and hence fewer adverse poverty effects.

The **CTY_TYPE** vector includes the 1990 county population. Besides accounting for the possibility of thicker labor markets with better employment matches, own population also proxies for a county's cost of living.[12] Another possible proxy would be to use average rental values to account for housing cost differentials, but by definition, such a variable would be endogenously determined with the share of the population living in poverty. However, we control for the key underlying exogenous (and predetermined) determinants of poverty including state fixed effects (described below) that account for amenity differentials and related cost of living differences.

The **DEMOG** vector includes demographic traits of the population commonly believed to be potentially correlated with poverty outcomes such as racial composition, average education, recent immigration status, single-headed household status, and age (Levernier et al., 2000). As noted above, these variables are measured at their 1990 levels (or 1980-1984 and 1985-1990 for the immigration variables) to avoid simultaneity. The education variables are the population proportions that have completed high school, completed some college but have no degree, have only an associate college degree, or a bachelors degree or higher. Because of its positive linkage with employment status and wage rates, higher education attainment should be associated with lower poverty. We expect the presence of single-headed households to increase poverty because the heads of these households typically possess fewer job skills, and there is typically only one earner in the household (Levernier et al., 2000). Likewise, if there are chained migration and beachhead effects, a higher initial immigrant share may indicate larger future increases in low-skilled labor supply. To the extent recent immigrants have higher poverty and compete with low-skilled natives (Borjas, 2003), a higher share of recent immigrants would increase the poverty rate.

α, θ, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\varphi}$ represent regression coefficients, whereas, σ_s denotes the state-fixed effect, and ε is the error term. Because county shocks may be transmitted to neighboring counties in an economic region, we also allow for spatial clustering of the residuals that may affect the t-statistics. Using the Stata cluster

[12] For example, Gyourko and Tracy (1989) found that variation in population is a strong proxy for regional differentials in cost of living. Also see footnote 2.

command, we assume that county residuals are correlated within their economic region, but independent of county residuals in other regions. We use the U.S. Bureau of Economic Analysis's 179 economic regions to denote our functional economic areas.[13] State fixed effects capture specific factors common across counties in each state including tax, expenditure, and welfare policies. Given the inclusion of state fixed effects, the regression coefficients reflect *within*-state variation in the explanatory variables, while cross-state effects are subsumed into the state fixed effects.

4. Empirical Results

In our empirical approach, we first estimate a very parsimonious model that only includes distance variables, own-county population, and state fixed effects. We view the estimates from this model as the upper-bound poverty effects of distance. Then, additional county attributes are successively added to the specification. This is done to assess robustness of the urban proximity coefficients and to appraise the interaction of proximity with these other county characteristics. For example, distance may partly underlie employment growth differences. Thus, the employment growth coefficient will capture some of the poverty effects of distance. Yet, if distance and job growth are correlated but not causally linked, omitting employment growth would bias the distance coefficients upwards. We conclude our analysis by adding other urban-proximity indicators to test more complex labor-market hypotheses of rural-urban interactions. In addition, we also assess our assumption that the underlying poverty generating processes for urban and rural poverty rates are inherently different, especially regarding proximity in the urban hierarchy.

The descriptive statistics for the 2204 nonmetropolitan counties and the 824 metropolitan counties are respectively reported in columns (1) and (2) of Table 1. They reveal that nonmetro poverty rates as determined by the U.S. Census Bureau were on average over 4 percentage points higher than MA poverty rates in 1999 and over 6 points higher in 1989. The typical nonmetro county is about 90kms from the centroid of their nearest MA, while the center of the typical metropolitan county is about 22kms from the (population-weighted) center of their own MA. Job growth in MA counties for 1990-1995 and the

[13]An alternative approach is to assume a spatial autocorrelation in the error terms and estimate the model using standard spatial econometric approaches. Yet, Partridge and Rickman (2005) report that their nonmetropolitan county poverty results were essentially the same using this approach. Note the clustering approach has the key advantage of allowing a unique spatial correlation structure within each BEA region and it does not impose a specific spillover structure on the model, both of which would be drawbacks of standard spatial econometric approaches.

corresponding industry mix job growth for 1995-2000 exceeded that in nonmetro counties by two percentage points.

Column (3) of Table 1 shows the results from the most parsimonious regression model.[14] As expected, these results suggest that nonmetropolitan county poverty rates are positively related to distances from higher-tiered urban centers. The largest estimated marginal penalty per km is distance to the nearest MA (of any size), though the point estimate for access to a MA of at least 500,000 people is almost as large. A one standard deviation increase in distance from the nearest MA is associated with a 1.1 percentage point increase in the typical nonmetro county's poverty rate, all else constant. By contrast, a one standard deviation increase in incremental distance to reach the three higher tiered MAs (<250,000, <500,000, <1.5m) is associated with a corresponding 2.5 percentage point increase in the poverty rate—i.e., a one standard deviation increase in distance to *all* urban tiers is associated with a 3.6 point increase in the poverty rate. Thus, space and location is highly associated with rural poverty. Conversely, a one-standard deviation in the population of the nearest MA is associated with only a 0.24 percentage point decrease in the typical rural county's poverty rate, which supports the argument that proximity to MAs is much more important than marginal changes in the size of the nearest MA.

The strong influence of distance to the nearest MA suggests that access to urban labor markets appears to be important in helping disadvantaged rural families (which we consider further below). Yet, the greater overall importance of access to even larger metropolitan areas that are presumably beyond easy commuting distance suggests that it is the economic vitality of the rural community that is relatively more important. That is, better access to higher-tiered urban centers spurs growth in rural communities through stronger interregional input-output/trade linkages and ease in obtaining urban amenities and services (Partridge et al., 2006a, 2006b). Thus, it appears that rather than the direct urban *labor* market access for disadvantaged workers, it is the trickle-down growth effects of *broader* rural access to higher-tiered urban areas that primarily reduce rural poverty. Indeed, these trickle-down urban-growth (urban-spread) effects have also been observed in the international development literature (Lucas, 2001).

Model 2 adds the county's demographic variables to the model. In this case, the **PROXIMITY** coefficients are smaller in magnitude, though still statistically significant (at the 10% level or better). For

[14]Omitting the own-county population has almost an imperceptible effect on the remaining coefficients.

example, the proximity to the nearest MA coefficient is about one-third smaller than in Model 1. Generally, this pattern suggests that more remote rural counties have demographic characteristics that are associated with higher poverty rates—though it is unclear whether proximity to the urban center directly causes demographic self-sorting, or whether other factors are behind this demographic spatial distribution.

Model 3 adds the lagged 1989 own and average-surrounding county poverty rates to the model. Although the urban proximity variables are still significant at the 10% level, the magnitude of their coefficients generally decline even more between Models 2 and 3 than between Models 1 and 2. For example, the coefficient on distance to the nearest MA declines by over one-half in Model 3. This implies that the **PROXIMITY** variables are strongly correlated with lagged poverty rates. This correlation likely relates to the general persistence of long-term county poverty rates including the underlying institutional and historic causes (Partridge and Rickman, 2005)—i.e., proximity to urban areas may be one cause for particular institutions to form in rural communities (Henry et al., 1997).

Model 4 adds the county's economic variables to the model. These results suggest that county employment growth in both the first-half and the second half of the 1990s is inversely related to poverty rates (significant at the 10% level).[15] Moreover, the importance of the most-recent five-year employment conditions and the lagged five-year employment conditions illustrate that persistent growth is particularly helpful in reducing rural poverty—i.e., one good year is not sufficient to fully reach down into the lower parts of the skills distribution.

The magnitude of the **PROXIMITY** coefficients only slightly declined in Model 4. This suggests that urban proximity is more correlated with lagged poverty rates than with more recent economic conditions. With the numerous control variables added to this specification compared to Model 1, the estimated distance effects reflect approximately a "lower" bound estimate of the effects of proximity. These proximity estimates are derived *after* accounting for demographic attributes, past poverty, and recent job growth, which also may be causally linked to geographic proximity.

In Model 4, a one standard deviation increase in the distance to reach the nearest MA increases the county poverty rate by 0.3 percentage points, while a corresponding one standard deviation increase in the incremental distance to reach the three higher-tiered metropolitan areas increases the poverty rate by 0.6

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[15]Note that the difference in the magnitude of the coefficients partially reflects that actual 1990-95 employment growth and 1995-2000 industry mix growth are respectively measured as percentage change and rate of change.

percentage points.[16] In addition, distance to urban centers still has a stronger effect than marginal changes in the population of the nearest MA—i.e., a one-standard deviation increase in the size of the nearest MA is associated with only a 0.1 point decline in the rural county's poverty rate.

One of the key assumptions underlying our empirical specification is that urban county poverty rates have a different data generating mechanism than for rural county poverty rates. To explore this, column (7) estimates the model using the 824 metropolitan counties as the sample. Regarding the key distance results, there is a very different pattern in which proximity within the urban hierarchy has no statistically significant impact, all else being equal.[17] Likewise, there are other variables in which there is a considerably different effect between the rural and urban samples (e.g., the share of female headed families has a considerably larger impact in the MA sample). Thus, our key assumption of considering rural counties in isolation appears warranted, especially regarding the role of urban proximity.

Robustness and Alternative Spatial Hypotheses

Table 2 reports the results of alternative spatial hypotheses and sensitivity analysis. Column (1) reports the results of Model 5, which except for the employment growth variables, replaces the explanatory variables measured in the 1980s and 1990 with corresponding variables measured in the 1990s and 2000 (Models 6 through 8 again use the 1980s and 1990 variables). This specification assesses whether changes in the explanatory variables during the 1990s underlie some of the key results. However, except for population of the nearest MA, whose coefficient declined by about one-half, the **PROXIMTY** variable coefficients are similar using more contemporaneous control variables.

To further investigate if the significance of the distance variables partly relates to commuting and migration responses to the availability of jobs, we add to Model 4 the interaction of distance to the nearest MA area with the nonmetropolitan county's 1995-2000 industry mix growth, producing Model 6. Consistent with our hypothesis, this interaction has a negative coefficient. Job growth reduces poverty more when the county is farther from its nearest urban center. In addition, the F-statistic reported at the bottom of Table indicates that the two own-county industry mix growth variables are jointly highly

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[16] In the calculation, we included the marginal effects of the incremental distance to reach a MA of at least 1.5 million even though it was only significant at the 15% level because in subsequent models in Table 2, it is significant at the 10% level.

[17] In the MA sample, distance to the nearest MA simply reflects the distance from the population-weighted centroid of the county to the population-weighted centroid of its own MA. For one county MAs, this distance is zero. The notes to Table 1 indicate some added control variables in the MA model including indicators for central and suburban county.

significant. Using the mean value for own-county industry mix employment growth, it begins to reduce poverty at a distance of about 40 km from the nearest MA. In addition, the magnitude of the **PROXIMITY** variable coefficients generally increase with improved statistical significance.

We also examine more specifically whether urban employment *growth* spreads to the countryside, such as through producing job opportunities for the rural poor. This hypothesis differs from whether basic urban proximity affects rural county poverty rates because the proximity variables did not account for whether the most-proximate urban centers are growing. We consider this possibility by adding to Model 6 the 1990-2000 industry mix growth rate in the nearest MA and an interaction of this variable with distance to the nearest MA.[18] Although the 1990-2000 nearest MA industry mix employment growth variable is only statistically significant at the 15% level, the F-statistic reported at the bottom of the table indicates that the two MA employment variables are jointly statistically significant at the 5% level.

Thus, urban "spread" effects appear to reduce rural poverty, in which one likely avenue is through creating job-commuting opportunities. A one standard deviation increase in the nearest MA industry mix growth rate is associated with a -0.3 percentage points decrease in a rural county's poverty rate if it is immediately adjacent to the core of the urban center. However, at the mean distance of 90kms, the corresponding change in poverty is only -0.1 percentage points. Yet, illustrating that urban proximity is still important in other ways, the distance variable coefficients are virtually unchanged in this model compared to Model 6.

A final sensitivity test assesses whether a county's natural amenities correlate with the **PROXMITY** variables and the poverty rate. To assess this possibility, the USDA natural amenity measure is added to Model 7, forming Model 8. However, the amenity measure is insignificant in this model and the other results are essentially unchanged.

5. Summary and Conclusions

Using a novel approach for representing rural location relative to larger urban centers, we examined the nexus between poverty in rural counties and their geographical location within the urban hierarchy. We found *ceteris paribus* increases in rural poverty rates the more distant an area was from a

[18]We use the metropolitan industry mix growth rate to mitigate any endogeneity concerns from using the actual MA employment growth rate. The growth over the entire 1990s is used to allow for the possibility that it may take especially prolonged growth to trickle out to the rural areas and reduce poverty (also the MA results in column (7) of Table 1 suggested that a longer period may be necessary when considering MAs).

metropolitan area. Furthermore, higher poverty rates were found for increased incremental distances from metropolitan areas in each successively higher population tier.

We argue the positive link between rural remoteness and poverty occurs because of the attenuation of agglomeration benefits over distance and incomplete labor supply responses, producing a form of rural spatial mismatch. For example, distance may inhibit rural trade of goods with metropolitan areas, reduce job-commuting opportunities for rural residents, and reduce access to specialized urban services, which serves to decrease rural employers' demand for local workers. And combined with incomplete labor supply responses, greater distance produces significantly higher poverty results in remote rural areas — even after accounting for spatial differences in demographics and other attributes.

In additional analysis, job growth in the nearest MA was found to have favorable poverty-reducing impacts that attenuate with greater distance. Thus, some of the antipoverty benefits of close proximity to metropolitan areas relate to "spread" effects such as increased job-commuting opportunities. We also found that local employment growth has greater poverty reducing impacts in remote counties. This likely occurs because of smaller commuting and migration flows between remote areas and other areas; i.e., remote areas have a more inelastic labor supply.

So, although market forces appear to inhibit labor demand in remote areas, geographically targeted policy efforts to stimulate growth may produce large antipoverty benefits (Bigman and Fofack, 2000; Partridge and Rickman, 2005). In this sense, remoteness is an advantage. But market forces favoring growth in areas more proximate to larger urban centers may be difficult to overcome. One long-term antipoverty policy might consist of urbanization trickle down, in which improved access to urban labor markets reduce rural poverty (which is reinforced by stronger urban growth). Yet, because of limited labor mobility, place-based economic development is a complementary tool to fight poverty in remote regions along with people-based policies that augment the skills of low-skilled workers.

Policies to improve sustainable local rural development, for example, might include support for tourism and microfinance efforts that encourage local entrepreneurship. Improving access to larger urban labor markets may especially help disadvantaged rural workers. However, because lengthy commuting to urban job centers requires its own unique supports, policies need a place-based orientation (Partridge and Rickman, 2005). For example, long commutes require different kinds of transportation in remote rural

areas than in urban areas with access to public transport. Funding grants for the poor to purchase an automobile may be more advantageous in remote areas dependent on auto transport. Likewise, because access to quality daycare (with sufficient hours of service) may be more deficient in rural communities, more attention to its provision would be required. This suggests distance should not only be examined for its effects on rural poverty, but also used in the design of policies to reduce poverty in remote rural areas.

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Table 1. Descriptive Statistics and Base Regression Results[a]

	(1) Nonmetro Counties (std dev)	(2) Metro Counties (std dev)	(3) Model 1 Nonmetro (t-stats)	(4) Model 2 Nonmetro (t-stats)	(5) Model 3 Nonmetro (t-stats)	(6) Model 4 Nonmetro (t-stats)	(7) Model 4[*] Metro (t-stats)
1999 Poverty Rate	15.3	11.0	na	na	na	na	na
(Dependent Variable)	(6.6)	(4.8)					
Lagged 1989 Poverty Rate	18.4	12.3			0.52	0.53	0.63
	(7.9)	(5.6)			(22.78)	(24.79)	(19.33)
1989 Surrounding Cty	17.8	13.7			0.12	0.12	-0.01
Average Poverty	(6.4)	(5.4)			(5.18)	(4.91)	(0.76)
Dist to Nearest MA (kms)	89.9	21.7	0.019	0.013	0.006	0.005	-0.005
	(58.5)	(19.7)	(4.44)	(5.60)	(5.36)	(4.63)	(1.19)
Incremental Dist MA>250k	65.7	31.3	0.006	0.003	0.003	0.002	0.002
(kms)	(103.4)	(73.2)	(1.69)	(2.02)	(2.64)	(2.18)	(1.55)
Incremental Dist MA>500k	43.2	34.0	0.017	0.011	0.005	0.004	0.0006
(kms)	(67.7)	(64.2)	(4.65)	(5.65)	(4.39)	(4.05)	(0.56)
Incremental Dist MA>1.5m	91.0	86.5	0.006	0.003	0.001	0.001	0.0005
(kms)	(114.7)	(128.2)	(1.94)	(1.95)	(1.77)	(1.49)	(0.72)
Nearest MA 1990Pop	149,033	na	-1.8e-6	-1.4e-6	-1.0e-6	-9.2e-7	na
	(135,727)		(2.48)	(2.82)	(3.29)	(3.12)	
Nearest MA 90-00 Indmix Gr	0.168	na					
	(0.063)						
%1995-00 Own Cty Indmix	0.095	0.115				-12.8	5.6
Grth	(0.018)	(0.02)				(3.08)	(1.28)
1990-95 Own Emp Growth	10.4	12.4				-0.012	-0.024
	(19.5)	(11.0)				(1.88)	(3.63)
1985-1990 Structural Change[b]	0.070	0.060				-3.2	-4.6
	(0.03)	(0.02)				(1.20)	(1.49)
1990 Pop× 1995-00 Struct Chg	na	na				9.5e-5	1.2e-5
						(0.98)	(1.27)
1990 County Population	22,416	239,597	-1.5e-5	-2.1e-5	1.4e-6	-3.9e-6	-6.4e-7
	(20,746)	(478,619)	(2.45)	(4.50)	(0.43)	(0.70)	(1.64)
% Population that immigrated	0.3	0.9		-0.01	0.17	0.13	0.29
between 1985-1990	(0.7)	(1.4)		(0.04)	(1.08)	(0.80)	(1.81)
% Population that immigrated	0.2	0.6		-0.09	0.09	0.17	0.10
between 1980-1984	(0.6)	(1.1)		(0.27)	(0.41)	(0.75)	(0.38)
1990 %Not HS Graduate	32.5	25.1					
(age≥ 25yrs)	(10.3)	(8.2)					
1990 %HS Graduate	35.1	32.5		-0.43	-0.13	-0.12	-0.08
(age≥ 25yrs)	(5.9)	(6.2)		(7.73)	(6.07)	(6.16)	(2.80)
1990 %Some College, no	15.6	18.4		-0.33	-0.05	-0.03	-0.04
degree (age≥ 25yrs)	(4.4)	(4.1)		(6.65)	(1.79)	(0.99)	(1.29)
1990 %Associate College	5.1	6.0		-0.44	-0.10	-0.10	-0.07
Degree (age≥ 25yrs)	(2.2)	(1.7)		(5.79)	(2.09)	(2.17)	(1.12)
1990 %Bachelors Degree or	11.7	18.1		-0.20	-0.06	-0.03	-0.05
more (age≥ 25yrs)	(4.8)	(7.9)		(6.34)	(3.23)	(1.55)	(2.47)
1990 % of HHs female-headed	5.2	5.9		0.69	0.12	0.13	0.29
with children	(2.4)	(1.8)		(9.13)	(2.10)	(2.45)	(3.98)
1990 % of HHs male-headed	1.4	1.3		0.28	-0.05	-0.005	0.16
with children	(0.6)	(0.4)		(1.65)	(0.36)	(0.04)	(0.72)
1990%Pop African American	8.2	9.8		0.05	0.02	0.017	-0.006
	(15.1)	(11.8)		(2.83)	(2.15)	(1.81)	(0.63)
1990 %Pop Other Race	3.8	4.0		0.12	0.06	0.06	-0.06
(non Caucasian, Black)	(8.0)	(5.6)		(3.79)	(2.81)	(2.91)	(1.87)
1990 %Pop Hispanic	4.2	4.7		0.007	-0.02	-0.02	0.003
	(11.4)	(9.7)		(0.35)	(1.26)	(1.41)	(0.22)
1990 Age Shares[c]			N	Y	Y	Y	Y

State Indicators			Y	Y	Y	Y	Y
R^2			0.459	0.813	0.896	0.898	0.942
N	2204	824	2204	2204	2204	2204	824

a. In parentheses in columns (1) and (2) are standard deviations and in columns (3)-(7) are the absolute values of the robust t-statistics adjusted for clustering within each Bureau of Economic Analysis economic region using the Stata Cluster command for the estimation. There are 177 BEA economic regions in the lower 48 states, which are constructed to reflect functional economic regions. Several specific metropolitan county type variables are also in Model 4* (not shown): total metropolitan area population; single-county metropolitan area; large metropolitan area suburban; large metropolitan area central city; small metropolitan area suburban; small metropolitan area central-city county. A large metropolitan area is defined as a 2000 population greater than 1 million and central city counties include part of the named metropolitan central cities. Metropolitan counties are defined using 2000 Bureau of Economic Analysis REIS county definitions. The employment growth and structural change variables are derived from Bureau of Economic Analysis REIS data, whereas the remaining data are from the U.S. Census Bureau, 1990 and 2000 censuses. See Partridge and Rickman (2006) for more details of variables and sample construction.

b. The structural change index is the share of the county's employment that would have to change sectors in 1985 and 1990 so that there would be an equivalent industry structure in the two years. It is a similarity index defined as one-half the sum of the absolute value of the difference in one-digit industry employment shares between the two years.

c. Age shares include the percent of the population less than 7 years old, between 7-17, 18-24, 60-64, and 65 and over. The omitted category is the percent between 25-59 years of age.

Table 2. Sensitivity Analysis Regression Results[a]

	(1) Model 5[b] (2000 **X** var.) Nonmetro (t-stats)	(2) Model 6 Nonmetro (t-stats)	(3) Model 7 Nonmetro (t-stats)	(4) Model 8 Nonmetro (t-stats)
1999 Poverty Rate ***(Dependent Variable)***	na	na	na	na
Lagged 1989 Poverty Rate	0.47	0.52	0.52	0.52
	(22.54)	(24.92)	(24.93)	(24.60)
1989 Surrounding Cty Average Poverty	0.13	0.12	0.11	0.11
	(5.89)	(5.09)	(4.76)	(4.75)
Dist to Nearest MA (kms)	0.005	0.026	0.025	0.025
	(4.51)	(5.06)	(4.88)	(4.89)
Incremental Dist MA>250k (kms)	0.003	0.002	0.003	0.003
	(2.83)	(2.21)	(2.34)	(2.35)
Incremental Dist MA>500k (kms)	0.004	0.004	0.004	0.004
	(4.78)	(4.17)	(4.15)	(4.19)
Incremental Dist MA>1.5m (kms)	0.001	0.001	0.001	0.001
	(1.82)	(1.72)	(1.68)	(1.68)
Nearest MA 1990Pop	-4.2e-7	-9.8e-7	-8.8e-7	-8.8e-7
	(1.70)	(3.25)	(2.88)	(2.89)
Nearest MA 90-00 Indmix Gr			-4.17	-4.16
			(1.49)	(1.48)
Nearest MA Indmix Grth× Nearest MA Dist			0.033	0.033
			(2.23)	(2.21)
%1995-00 Own Cty Indmix Grth	-8.6	9.0	10.9	10.6
	(2.05)	(1.46)	(1.66)	(1.62)
Dist Near MA × %95-00 Own Indmix Grth		-0.224	-0.239	-0.240
		(4.16)	(4.15)	(4.13)
1990-95 Own Emp Growth	-0.007	-0.013	-0.013	-0.013
	(1.08)	(2.19)	(2.16)	(2.16)
1985-1900 Structural Change[c]	9.4	-3.8	-4.0	-4.1
	(3.34)	(1.43)	(1.50)	(1.50)
1990 Pop× 1995-00 Struct Chg	-0.0002	1.1e-4	1.2e-4	1.2e-4
	(2.25)	(1.13)	(1.20)	(1.21)
1990 County Population	9.8e-5	-6.6e-6	-6.6e-6	-6.6e-6
	(2.06)	(1.13)	(1.13)	(1.13)
Amenity Rank[d]				0.06
				(0.75)
Demographic Variables[e]	Y	Y	Y	Y
1990 Age Shares[f]	Y	Y	Y	Y
State Indicators	Y	Y	Y	Y
F-stat: $\beta_{\%1995\text{-}00\ Own\ Cty\ Indmix\ Grth} = \beta_{Dist\ Near\ MA \times \%95\text{-}00\ Own\ Indmix\ Grth} = 0$ (p-value)[g]		12.84 (p=.0001)	12.70 (p=.0001)	12.80 (p=.0001)
F-stat: $\beta_{Nearest\ MA\ 90\text{-}00\ Indmix\ Gr} = \beta_{Nearest\ MA\ Indmix\ Grth \times Nearest\ MA\ Dist} = 0$ (p-value)[g]			3.08 (p=.049)	3.04 (p=.050)
R^2	0.914	0.899	0.900	0.900
N	2204	2204	2204	2204

a. In parentheses are the absolute values of the robust t-statistics adjusted for clustering within each Bureau of Economic Analysis economic region using the Stata Cluster command for the estimation. See the notes to Table 1 for details.
b. Model 5 uses 1999/2000 values of the explanatory variables or relevant 1990-1994/5 and 1995-2000 values.
c. See note b in Table 1.
d. A 1–7 amenity ranking that is positively related to natural amenities. The ranking is developed by the Economic Research Service of the U.S. Department of Agriculture.
e. The same demographic controls shown in Table 1.
f. See note c in Table 1.
g. See text for more details.