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**Persistent Pockets of Extreme American Poverty:  
People or Place Based?\***

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**Abstract.** Over the past four decades almost 400 U.S. counties have persistently had poverty rates in excess of 20 percent. These counties are generally characterized by weak economies and disadvantaged populations. This raises the hotly debated question of whether poverty-reducing policies should be directed more at helping people or helping the places where they reside. Using a variety of regression approaches, including geographically weighted regression analysis, we consistently find that local job growth especially reduces poverty in persistent-poverty counties. We also find that persistent-poverty counties do not respond more sluggishly to exogenous shocks, nor do they experience more adverse spillover effects from their neighboring counties. Finally, we identify some key geographic differences in the poverty determining mechanism among persistent-poverty clusters. Taken together, these results indicate that place-based economic development has a potential role for reducing poverty in these counties.

**JEL: I32, I38, R23**

**Keywords: Poverty; Persistent Poverty; Economic Development Policies; Place-Based Policies**

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## 1. Introduction.

Despite significant progress in the 1960s, and two of the three longest U.S. economic expansions on record in the 1980s and 1990s, the 2003 U.S. Census Bureau poverty rate of 12.5 percent exceeded that registered in 1973 (11.1 percent).<sup>1</sup> Moreover, the poverty rate in the intervening three decades has more often been above the 12.5 percent rate than below it. Even more discouraging is that there remain large clusters of deep poverty in: the Mississippi Delta, the historic Southeastern Cotton belt, areas near the Rio Grande, central Appalachia, and Western American Indian Reservations. Of just over 3,000 counties, 494 had a poverty rate exceeding 20 percent in 1999.

It is especially troublesome that 382 counties had poverty rates exceeding 20 percent in each of 1959, 1969, 1979, 1989, and 1999 (Miller and Weber, 2004)—earning the title “persistent poverty” (PP) counties by the U.S. Department of Agriculture (USDA). Easterly (2001) contends that most of these high-poverty clusters have many commonalities with “ethno-geographic poverty traps” found in developing countries (e.g., the Northeast of Brazil or the Chiapas in Mexico); though it is likely the underlying dynamics differ. Indeed, the clusters in the Deep South have high Black population shares; those in the Southwest have high shares of Hispanics, while their counterparts in the West have high shares of Native Americans (USDA, 2004). Only the Appalachian/highland group is characterized as having mostly Whites.

Despite occurring in such a wide variety of geographic clusters, the spatial dimension of persistent American poverty has not been empirically explored. These clusters could suffer from many impediments including weak community capacity and governance, poor economic opportunities, and significant shortfalls of human and physical capital (Glasmeier and Farrigan, 2003). The rural, often remote nature of most PP counties suggests that they also may lack the critical mass to sustain economic activity. Therefore, despite the attention given to poverty clusters in developing economies (e.g., Ravallion and Woden, 1999; Lucas, 2001), it is surprising that the question of whether persistent pockets of American poverty are more people-

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<sup>1</sup>For more details of the dating of U.S. business cycles, see the National Bureau of Economic Research at [www.nber.org](http://www.nber.org). The U.S. poverty rates can be found at the U.S. Census webpage at <http://www.census.gov/hhes/poverty/histpov/hstpov2.html>.

based or place-based has been largely ignored. The answer would address whether antipoverty policies should focus primarily on helping *people*, or also on improving conditions in their *place* of residence.

Therefore, this study examines 1999 poverty rate determinants using Census 2000 data for the roughly 3,000 U.S. counties. The focus will first be on differences between persistent poverty (PP) counties and the remaining counties to examine if economic conditions have a stronger poverty impact in PP counties. If so, this would support those who argue that place-based policies are needed components of antipoverty efforts. Then, once establishing differences between PP counties and non-PP counties, using geographically weighted regression (GWR) analysis, we assess the spatial differences in the underlying causes of poverty across the various poverty clusters. The results not only have implications for fighting poverty in PP clusters, they also have implications for the geography of economic development policies in general.

In what follows, the next section outlines the literature on place- and people-based poverty. Section 3 describes the empirical model and data, while section 4 presents and discusses the results. The paper concludes with a summary of the findings and their policy implications.

## **2. Place-Based and People-Based Policy**

Figure 1 shows counties possessing poverty rates exceeding 20 percent in 1969, 1979, 1989, and 1999. The four ethno-clusters described in the Introduction are apparent. In addition, almost all PP counties are nonmetropolitan and generally located far from large urban centers. Yet, it is not *a priori* clear whether antipoverty policies should be place-or people-based.

A high degree of labor mobility argues against place-based policies since mobile labor should arbitrage away geographic utility differentials (Ravallion and Wodon, 1999; Partridge and Rickman, 2003). Thus, it is not surprising that economists often contend that *place* policies such as subsidies and tax breaks aimed at distressed communities are wasteful. They argue that place-based policies create a culture of dependency that dampens incentives including those that would induce the disadvantaged to relocate to better job opportunities (Glaeser, 1998). Though there may be many willing potential workers in a poor community, place-based policy critics also argue that most of the newly created jobs in a poor community would instead go to more

qualified commuters and newly relocated residents and not the intended beneficiaries (Peters and Fisher, 2002). Instead of place-based policies, they prefer person-based policies such as education and training, job counseling, and relocation assistance.

Additional factors argue against place-based policies in poverty clusters if they are remote or of small scale because that may inhibit economic development due to “backwash” effects of economic activity being drawn to urban centers (Barkley et al., 1997; Henry et al., 1997). In addition, public service provision often involves scale economies, which can lead to small areas possessing insufficient public infrastructure to be economically competitive (Lucas, 2001; Jalan and Ravallion, 2002; Glasmeier and Farrigan, 2003). Small, remote areas are at a further disadvantage if high-skilled labor is relatively more mobile; the exodus of high-skilled labor from PP counties may lower the pay of those remaining (Gibbs, 1994). These factors may combine to make it difficult for PP counties to escape high-poverty status, which is somewhat akin to “poverty traps” in developing countries (Lucas, 2001; Jalan and Ravallion, 2002).

Arguing against a people-based approach are several factors that may contribute to limited labor mobility between PP and lower-poverty counties. Foremost, disadvantaged households and workers with less human capital are not as geographically mobile (Ravallion and Wodon, 1999; Yankow, 2003). In addition, given the remoteness of many PP counties, greater distance to potential migration destinations increases transport and psychic costs of relocation (Greenwood, 1997). Impoverished individuals in PP counties also may simply move to other high poverty counties because that is where low-skilled workers may be most in demand (Lucas, 2001). Thus, unless one accepts that PP county residents have determined that they are currently as well off in their current location as elsewhere, solely relying on people-based policies may be inadequate in addressing the spatial concentration of poverty (Blank, 2004).

In addition, if growth could be stimulated in remote PP counties, and if labor mobility was limited, growth would lead to significantly greater poverty reduction. For example, potential migrants or in-commuters may be unwilling to take work in these counties or are simply unaware of emerging economic opportunities in these regions compared to larger urban centers. Fewer new migrants and commuters taking the new jobs leave more of the benefits for the intended

disadvantaged beneficiaries, consistent with arguments for place-based policies. Thus, while remoteness or small scale may be a drawback in many contexts, it might have the advantage that own residents will garner more of the benefits if economic development did take hold.

The drawbacks of people-based policies suggest the need for place-based policies. Place-based policies derive their appeal from the notion that wide spatial variation in local attributes thwart “one-size-fits-all” policies. Place and related contextual effects influence economic vitality and shapes the character of the people (Blank, 2004). In isolated inner cities and remote rural areas, many of the disadvantaged have less access to job training, counseling, healthcare, childcare, and transportation, suggesting that government-service delivery should reflect these spatial differences (Allard et al., 2003). Even in instances where person-based approaches may be appropriate, advocates of place-based policies argue they have an important complementary role (Blank, 2004). For example, work-support policies such as the provision of childcare, transportation, and training may have higher payoffs if jobs are nearby.

Place-based policy advocates also argue that economic development policies can effectively enhance local growth because of factors such as neighborhood effects, economic-role models, and knowledge spillovers. Finally, place-based policies have the simple advantage that governments may find it easier to target poor places than to identify households with the specific attributes that would merit targeting (Ravallion and Wodon, 1999). Along with the fact that voters are also “place-based,” another practical factor is that political constituents may find it more appealing to target locations than people.

The long duration and spatial concentration of persistent poverty counties provide a good empirical test of whether place-based policies that improve job growth can reduce poverty. Supporting the use of people-based policies, residents of PP locales typically possess attributes that place them at higher risk of poverty, suggesting that improving their personal attributes should be the policy target. Yet, PP regions also lack the requisite economic opportunities that could lift impoverished households above the poverty threshold. To be sure, if there is anywhere in the U.S. in which place-based impediments inhibit favorable outcomes, it is in PP counties. Thus, we hypothesize that *ceteris paribus* increases in job growth will have proportionately

larger poverty-reducing effects in PP counties. Nevertheless, those who support only people-based policies counter that without stronger human capital and labor-market attachment, the benefits from job opportunities would likely flow to unintended beneficiaries who already have the necessary skills and experience that employers prefer (e.g., commuters, migrants, or new labor-force entrants from more financially secure households). Below, we formulate an empirical approach to shed further light on the issue.

### **3. Empirical Model.**

The empirical model generally follows past spatial studies of overall poverty rates such as Madden (1996), Levernier et al. (2000), and Gundersen and Ziliak (2004). The basic model accounts for labor market factors that affect wages and labor-force participation, as well as demographic characteristics of the population. A partial (disequilibrium) adjustment formulation allows for the possibility that poverty responses are sluggish and a function of past poverty rates.

Each county has its own expected (equilibrium) poverty rate given its demographic and economic characteristics, in which changes over time in the underlying characteristics would also change the expected (equilibrium) poverty rate. Economic shocks can also change the expected poverty rate. It may take time for the economy to adjust to the shocks and for the actual poverty rate to adjust to the expected rate. Given the prevalence of economic (and possibly demographic) shocks, it is unlikely that in any given year the actual county poverty rate equals the expected rate. So, the current poverty rate is a function of the characteristics that determine the expected poverty rate, and the lagged poverty rate to account for disequilibrium adjustment. Note that one advantage of controlling for the lagged poverty rate is that also helps control for any “fixed effects” that persistently lead to a high or low county poverty rate, *ceteris paribus*.

Table 1 lists the variables used in the empirical specification and their sources. The causal variables are fairly self-explanatory, in which most of our attention will be on the role of economic variables, especially job growth, along with the lag of the own-poverty rate and average surrounding-county poverty rate to assess the effects of persistence and clustering/spillovers. The following model is estimated separately for PP counties and for non-persistent poverty counties (county  $i$  in state  $s$ ):

$$(1) \text{POV}_{is1999} = \alpha I \text{POV}_{is1989} + \theta I \text{AVGNEIGHBORPOV}_{is1989} + \boldsymbol{\varphi 1} \text{ECON}_{is} + \boldsymbol{\beta 1} \text{CTY\_TYPE}_{is} \\ + \boldsymbol{\gamma 1} \text{DEMOG}_{is} + \sigma_s + \varepsilon_{is}.$$

The dependent variable is the overall 1999 county person poverty rate. For the explanatory factors, AVGNEIGHBOR is the average 1989 poverty rate in contiguous counties (can include both PP and non-PP counties), which picks up spillover/clustering effects. The **ECON** vector contains county-economic performance measures, including, job growth, employment-population and unemployment rates, the degree of industry restructuring, and the percent of workers employed full-time.<sup>2</sup> We are primarily interested in the effects of economic development, which is generally perceived to be employment growth by policymakers (Bartik, 2001). Thus, to fully identify job growth's complete direct and indirect effects on poverty, our base model will include just job growth as the primary economic measure. Other economic measures are added in subsequent models to help trace employment growth's indirect effects on poverty rates (e.g., by reducing unemployment and increasing full-time work). Yet, when these economic measures are included, economic development's net impact will be harder to identify as the growth effects will be dispersed through the other economic variables (versus considering job growth in isolation).

The **CTY\_TYPE** vector has county-type (e.g., suburban or rural) and population measures. The **DEMOG** vector includes demographic traits of the population such as racial composition and average educational attainment.  $\alpha I$ ,  $\theta I$ ,  $\boldsymbol{\beta 1}$ ,  $\boldsymbol{\gamma 1}$ , and  $\boldsymbol{\varphi 1}$  represent regression coefficients, whereas,  $\sigma_s$  denotes the state-fixed effect, and  $\varepsilon$  is the error term. State fixed effects capture specific factors common across counties in each state including tax, expenditure, and welfare policies. With state fixed effects included, the regression coefficients reflect within-state variation in the explanatory variables; cross-sectional effects are subsumed into the state fixed effects.

If place-based factors influence poverty rates, it would be reasonable to believe that the causal mechanism of place-based factors varies across different poverty clusters. First, racial composition and other characteristics differ across the poverty clusters. Black PP clusters have high shares of female-headed families with children. Hispanic PP clusters have high shares of recent immigrants

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<sup>2</sup>Theory does not provide guidance as to the timing of the linkage between job growth and poverty. Experimentation with various time periods revealed that five-year (1995-2000) measures were superior to those from other periods, which were often highly insignificant.



and low high school completion rates. Native American clusters have the highest poverty rates with very low employment/population ratios, while White-highland PP clusters also have low educational attainment (USDA, 2004). Moreover, different racial compositions also may produce differential migration propensities or institutional and cultural arrangements.<sup>3</sup>

Differing geographic settings also may relate to differential poverty-generating processes. For example, some clusters are more remote from large urban centers. This may contribute to greater cultural and economic isolation. Remoteness may also be associated with lower rates of gross migration flows. Thus, to examine whether the underlying causes of poverty vary across the various PP clusters, we employ a GWR approach to assess whether the regression parameters vary across space using software described by Fotheringham et al. (2002).

The GWR approach weights the explanatory variables in “neighboring” counties to produce spatially distinct regression coefficients for each observation (Fotheringham et al., 2002).<sup>4</sup> The weight placed on neighboring counties is inversely proportional to their distance from the county of interest. The number of neighboring counties or bandwidth used in the estimation of the individual county regression coefficients is endogenously selected to minimize the Akaike information criterion (AIC) (see Fotheringham et al., 2002 for details). The GWR process can be represented for county  $i$  in state  $s$  located in location  $g$  as:

$$(2) \text{POV}_{is1999}(g) = \pi 1(g) + \boldsymbol{\pi} 2(g) \mathbf{X}_{is} + e_{is},$$

where  $\pi 1$  is a constant term for each county,  $\mathbf{X}$  contains the continuous variables from equation 1, with  $\boldsymbol{\pi} 2$  denoting the corresponding coefficients for each county. The regression coefficients for each county equal:

$$(3) \boldsymbol{\pi} = [\mathbf{X}'\mathbf{W}(g)\mathbf{X}]^{-1}\mathbf{X}'\mathbf{W}(g)\mathbf{Y}.$$

The individual  $w_{is}(g)$  are estimated using a Gaussian process  $\exp(-d/h)^2$  with  $d$  being the distance from the neighboring county and  $h$  denoting the bandwidth reflecting the number of neighboring (local) counties used in the estimation process. Specifically,  $h$  is the distance to the furthest

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<sup>3</sup> For example, Blacks generally have a lower propensity to migrate (Spilimbergo and Ubeda, 2004), there appears to be differences in the propensity to form ethnic enclaves among Hispanics (Stoll, 1999), and differing institutional arrangements on Native American reservations (Leichenko, 2003).

<sup>4</sup>The GWR approach is a subset of local-weighted regression techniques. Another example of a GWR/local weighted regression study is McMillan’s (2003a) examination of Chicago neighborhood home sales.

observation included in the local sample. A Monte Carlo procedure is then implemented to test whether the individual coefficients spatially vary across the entire sample.

The GWR approach has other advantages besides capturing spatial heterogeneities in the regression coefficients. First, because each county has its own intercept term, there is no need to estimate specific county fixed effects or add dummy shifters for factors such as being a metropolitan county. Second, because the regression coefficients are tied to a specific location, they can be mapped to assess whether there are spatial patterns in the coefficients across the various PP clusters. Third, a GWR approach more directly addresses spatial dependence issues than is the case in other spatial-econometric approaches that account for spatial autocorrelation and spatial autoregression (Fotheringham et al., 2002). The county-specific constant term (fixed effect) uses information in surrounding counties in its derivation. Likewise, spatial correlation in the error terms could reflect high spatial correlation in the explanatory variables and heterogeneity in the corresponding regression coefficients. The county-specific regression coefficients address this heterogeneity problem (see footnote 11).

#### **4. Empirical Results**

The descriptive statistics in columns (1) and (2) of Table 1 reveal that PP counties are at a distinct disadvantage. Consistent with a lack of place-based opportunities, they had about one-half the average 1995-2000 job growth of the other counties, more structural change, average employment-population rates about 10 percentage points lower, and average unemployment rates about 4 points higher. Consistent with clustering effects, PP counties are surrounded by counties whose lagged average poverty rate was over 11 percentage points higher. Yet, high poverty in PP counties could simply reflect unfavorable person-based demographic traits associated with higher poverty. They had nearly twice the average adult population share that did not complete high school, and much greater shares of minorities and female-headed families with children. Thus, assessing the role of place in poverty requires controlling for these demographic attributes.

##### *Standard Regression Analysis*

Columns (3)-(4) report the regression results for PP counties, and columns (5)-(6) show the corresponding results for the sample of other counties. The base models are reported in columns

(3) and (5), in which five-year employment growth is the only labor demand measure. The remaining columns in Table 1 report the results of including additional labor-market measures to disentangle the indirect channels through which job growth affects poverty.<sup>5</sup>

In the base models, the coefficients on the 10-year lagged poverty rate for both the PP and non-PP county samples are large and statistically significant, suggesting that they both undergo a somewhat sluggish adjustment to exogenous shocks.<sup>6</sup> Yet, PP counties are not necessarily at a greater disadvantage because both samples of counties exhibit approximately the same responses to lagged 1989 poverty rates. So, the relative persistence of poverty is more attributable to persistence in the determinants of poverty in PP counties.<sup>7</sup>

Both PP and non-PP counties are positively affected by lagged average surrounding county poverty rates. This pattern is consistent with a favorable clustering effect for non-PP counties and an unfavorable clustering effect for PP counties. A one-percentage point higher surrounding-county poverty rate raised own-county poverty rates by 0.11 points and 0.09 points, respectively, for PP and non-PP counties. Therefore, although PP counties suffer from being surrounded by counties with higher poverty rates, the relative size of the responses to neighboring county poverty are about the same across samples.

The results also suggest that for every one-percentage point increase in the five-year job growth rate (or about 0.2% more per year), the poverty rate falls an average of 0.066 points in PP counties, or almost three-fold more than non-PP counties. This difference is significant at the 1 percent level based on a one-tailed test, which is notable given that a myriad of demographic (person-based) factors are accounted for.<sup>8</sup> The difference across samples in the relationship

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<sup>5</sup>A Chow test of the base specifications supports the argument that the underlying causal mechanism determining poverty rates in PP and non-PP counties significantly differs ( $\chi^2(58)=471.8$ ,  $p=.0000$ ).

<sup>6</sup>In partial adjustment models such as this, the long-run responses are simply derived from the coefficients on the lagged poverty rate variable. For the PP model, the long-run responses will be 1.667 times the regression coefficients ( $1/(1-0.40)$ ), while for the non-PP model the coefficients will be 1.786 times larger ( $1/(1-0.44)$ ).

<sup>7</sup>One concern is that poverty in PP counties is so severe that it would begin to reduce productivity and employment growth. Such endogeneity would negatively bias the PP county employment growth coefficient. We tested this possibility with a Hausman test using the predicted 1995-2000 industry mix job growth rate from shift-share analysis as the identifying instrument. Industry-mix employment growth is commonly used as an instrument because it applies *national*-industry employment-growth rates to the county's industry composition, which is a measure of exogenous shifts in labor demand (Blanchard and Katz, 1992). The Hausman test suggested that this endogeneity was not a concern ( $t=0.03$ ), whereas the industry mix variable was highly significant in the first-stage model ( $F=10.43$ ), suggesting it was a good instrument.

<sup>8</sup>The calculated t-statistic equaled 2.37, and was calculated as the difference between the two coefficients divided

between employment and poverty is attributable to differential probabilities of residents being lifted out of poverty and is not a statistical artifact of differences in initial poverty levels.<sup>9</sup>

Thus, place-based economic development programs that successfully stimulate employment may have considerably greater poverty reducing effects in PP counties. A likely explanation is that job growth in PP counties is much less likely to attract migrants or commuters. This may occur because of uncertainties about the region's long-term economic viability, as well as a lack of information given these regions' general isolation, which increases the probability new jobs lift existing residents out of poverty. Likewise, in the face of economic declines, residents of PP counties may be less likely to out-migrate and have fewer out-commuting work opportunities.

Because industry composition likely differs between PP and remaining counties, we re-estimated the base model by adding industry employment shares (not shown). The results continue to suggest that job growth has much more of a poverty reducing effect in PP counties than in non-PP counties (respective employment growth coefficients: -0.050 ( $t=3.10$ ) and -0.020 ( $t=4.19$ )). A stronger job-growth response is found despite the likelihood that an underperforming industry composition likely underlies some of the poor job growth in PP counties, in which this collinearity steals away some of the employment-growth response.

Despite potentially being tempered by net in-migration, job growth likely reduces poverty rates by increasing the population share that is employed, reducing the unemployment rate, and raising the share of fulltime employment. Thus, to better understand the channels through which employment growth reduces poverty, the models reported in columns (4) and (6) include industry shares and measures of residential mobility and labor-market tightness. The results provide evidence of employment growth both, directly reducing poverty, and indirectly reducing poverty through increased labor-market tightness.

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by the square root of the sum of the estimated coefficient variances.

<sup>9</sup>Abstracting from population change and existing worker effects for the moment, the percentage-point change in poverty ( $\Delta\text{pov}$ ) depends on the probability each new jobs lifts a person out of poverty ( $\text{pr}(\text{exit})$ ), and the increase in the employment rate, which is given by the employment growth rate ( $g$ ) multiplied by the initial employment rate ( $er$ ):  $\Delta\text{pov}=\text{pr}(\text{exit})(g)(er)$ . For equal values of  $\text{pr}(\text{exit})$  and  $g$ , we would expect a lower percentage-point poverty rate change for high-poverty counties if they are associated with lower initial employment rates. In addition, since we account for demographic effects, including education, as well as state fixed effects (and lagged poverty effects), the primary differences in  $\text{pr}(\text{exit})$  should relate to differences in growth-induced migration and commuting responses between PP and the remaining counties. So, the greater percentage-point change in poverty for PP counties indicates their greater probability of residents exiting poverty ( $\text{pr}(\text{exit})$ ) because of growth.

Beyond its impact on labor-market tightness, the results indicate that five-year job growth has statistically significant poverty-reducing effects in which its coefficient continues to be about three-times larger than in the non-PP model. Yet, reflecting the smaller *direct* job-growth response, the difference between the PP and non-PP models is only significant at the 10 percent level (one tailed,  $t=1.37$ ). That is, including the other labor-market variables take away employment growth's indirect influence, reducing the magnitude of its coefficient. Nevertheless, the employment growth response is still almost one-half as large as in the base models in columns (3) and (5), suggesting that job growth reduces poverty in ways besides increasing labor-market tightness. Possibilities include “hysteresis” effects such as, occupational upgrading, increased work experience and training, and greater self-confidence, which lead to long-term income gains for the disadvantaged that go beyond simply finding work (Bartik, 2001).

Regarding the labor tightness results, it appears that the indirect poverty effects of greater job growth in PP counties occur more by raising male and female employment-population rates and less by reducing unemployment rates. Given the inclusion of demographic characteristics to account for supply-side influences, these counties appear to generally suffer from a “shortage” of jobs that is not simply reflected by the official unemployment definition, which is again consistent with place-based policies being a potential way to alleviate poverty in PP clusters. It seems plausible that large numbers of potential workers have simply given up searching for work in PP counties. Conversely, these results suggest that disadvantaged jobless men are more likely to be officially unemployed in non-PP counties, which is reflected by the positive and significant male-unemployment rate coefficient.

Most of the other results are similar between the two types of counties. Yet, one change is that PP counties have a significantly *smaller* 10-year lagged poverty rate response ( $t=2.14$ ), suggesting that PP counties are *not* severely trapped in high poverty due to a slow adjustment mechanism. In fact, a smaller lagged poverty rate response means that PP county poverty rates respond faster to positive changes in their underlying conditions. On a less favorable note, PP county poverty rates are about twice as adversely affected on average by industry structural change between 1995-2000 (as measured by an industry-composition dissimilarity index when

population is zero), which may be related to lower labor mobility and a lack of nearby commuting opportunities.<sup>10</sup> Yet this again points to the potential need for place-based policies. Another difference between the PP and non-PP models is the shares of single male- and female-headed households with children had more adverse effects in PP counties, possibly related to a relative lack of childcare support. But the general similarity of demographic results between the two samples suggests that person-based effects have similar causal mechanisms on average.

*Alternative specifications.*

Using the base specifications in columns (3) and (5), which estimate the total effects of job growth, Table 2 reports the results of several alternative specifications to test for robustness. First, Panel A reports the results of replacing the overall poverty rate with the percent of the population living in households below 50 percent of the poverty threshold, whereas Panel B does the same using the percent of the population between 50-100 percent of the poverty threshold. In both cases, the responses to the lagged poverty rate and the average surrounding county poverty rate are about the same for PP and non-PP counties. Also, it is not surprising that the responsiveness to job growth is about one-half the size in Panels A and B than the corresponding overall result in Table 1 because the poverty population has been split. Yet, the point estimate for the job growth variable remains about two to three times larger for PP counties than non-PP counties. It is especially encouraging that job growth has such a strong poverty-reducing impact for even the most economically deprived PP-county households because it is likely their members face the strongest labor-force impediments.

Another issue is how far up the income distribution does job growth benefit low-income households. To examine this, Panel C reports the corresponding results using the percent of the population living between 100-150 percent of the poverty distribution. In this case, job growth has a more ambiguous *a priori* impact because it lifts some of those below poverty to just above the poverty line, and it lifts some of those in the 100-150 percent category further up the income

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<sup>10</sup>The population-structural change interaction accounts for the possibility that more populous labor markets have better/more labor-market matches for laid-off workers. In fact, the results in column (6) suggest that in non-persistent poverty counties with over 279,000 people, poverty is no longer adversely affected by structural change. Yet, there are no significant mitigating effects from greater population in PP counties.

distribution. Thus, it is not surprising that the results suggest that job growth has almost no estimated impact for PP counties, suggesting the two effects offset. Yet, for non-PP counties, job growth reduces the share living between 100-150 percent of poverty, indicating broader impacts up through the income distribution, while the impacts below the poverty line are more limited.

Panels D, E, and F report sensitivity analysis when various interactions with job growth are added to the base models reported in columns (3) and (5) of Table 1 (see the notes to Table 2 for more details). First, Panel D reports on whether there are differences in the poverty responsiveness to job growth in counties that have been historically more reliant on primary goods or manufacturing production. Panel E tests whether job growth's effects have different effects in PP counties that have historically had tighter labor markets using an above-average 1990 male and female employment rate as the measure of historic tightness. Namely, if a labor market has generally been tighter, new job growth may disproportionately go to disadvantaged individuals who are marginally attached to the labor market. Panel F tests whether the effects of job growth differ depending on the county's educational composition. For example, job growth may have its strongest poverty reducing impacts when the workforce has a relatively low educational attainment because employers would be forced to hire the more disadvantaged.

In all three cases, the additional employment interactions are nowhere close to being jointly statistically significant in the PP specifications. So, economic development policies that stimulate employment growth can be successful in reducing poverty across a wide range of PP counties regardless of their characteristics—i.e., PP counties may not be hopeless “poverty traps.” For non-PP counties, only the education-job growth interactions are jointly significant, though the magnitude is sufficiently small to be of little practical importance.

#### *The Geographical Heterogeneity of PP County Responses.*

Sensitivity analysis suggested that spatial autocorrelation might be present, though further investigation suggested that regression results were essentially unchanged when correcting for spatial autocorrelation.<sup>11</sup> Thus, we did not pursue the spatial autocorrelation corrections further.

<sup>11</sup>Spatial autocorrelation may exist because a labor-demand shock in a county spills over and affects neighboring county labor markets. Another type of spatial dependence arises when there is slight spatial heterogeneity in the underlying parameters, which GWR techniques address. For instance, the determinants of poverty rates in rural Mississippi and rural Iowa counties likely differ somewhat. Similarly, there is usually a positive spatial correlation

Yet, as described in the previous section, there are reasons to expect that the actual regression coefficients vary across the counties, and in particular, across the various poverty-cluster groups. To explore this possibility, using the 381 PP counties, we estimated a geographically weighted regression (GWR) model for the column (3) specification (net of the other dummy variables that are in the county-specific intercept). The GWR regression results are summarized in Table 3.

The F-statistic reported at the bottom of Table 3 tests the null hypothesis that introducing spatial variation into the model's parameters did not improve the overall fit. The null was rejected at the 0.1 percent level, suggesting that the GWR approach is appropriate. Moreover, the AIC test procedure was minimized when the local sample size equaled 371.<sup>12</sup> Thus, while the nearest PP-county neighbors received the most weight, the procedure still used almost the entire sample of 381 PP counties in estimating the individual county coefficients. By contrast, if all 3028 counties would have been pooled into a model and estimated by GWR, the local sample for each county would have been based on the nearest 510 counties (not shown). This means that for PP counties, which tend to be dispersed throughout the country, the typical local PP-county sample would have included several hundred non-PP counties and relatively few PP counties. One outcome is much of the PP/non-PP heterogeneity would have been washed out, much like what usually occurs when pooling a quite small distinct sample with a much larger sample.<sup>13</sup>

The first column of Table 3 reports the p-values for the Monte Carlo test of the null hypothesis that the individual regression coefficients do not spatially vary across the 381 PP

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in the explanatory variables (e.g., rural Mississippi counties tend to have low average education and more minorities and the opposite is true for rural Iowa). Together, there will also be a positive correlation between the residuals (e.g., the model consistently over (under) forecasts poverty in rural Iowa (Mississippi)), although this has more to do with a slight misspecification due to pooling rather than an economic mechanism of shocks spilling over to nearby counties. The models reported in Tables 1 and 2 pool counties to obtain an average effect for each grouping and increase efficiency, but estimating a uniform national effect produces a loss of information when there is spatial heterogeneity in the responses. However, standard spatial autocorrelation tests will be unable to identify whether the spatial autocorrelation is due to spatial heterogeneity in both the specification and explanatory variables, which would require a GWR approach, versus an economic process of shocks spilling over to nearby counties, which would require a spatial autocorrelation correction (also see McMillen, 2003b, 2004).

<sup>12</sup> To test the robustness of the local sample size selected by the AIC calibration, a cross-validation (CV) technique was used to select the local bandwidth (Fotheringham, et al., 2002). Yet, the CV approach also yielded an optimal local sample size of 371. Likewise, we tested the robustness of the results by imposing a local sample size of 185, which is one-half of 371. Nevertheless, the general pattern of the results was qualitatively unchanged.

<sup>13</sup> Illustrating how the pooled 3028 county sample can wash out heterogeneity even when employing GWR, the absolute *largest* five-year job growth response for a county when using the entire pooled sample was -0.078, and the p-value for the test that there was no spatial variation in the county job-growth coefficients was 0.58. Conversely, Table 3 shows that the *median* PP-county 1995-2000 job-growth coefficient equals -0.077 when using GWR.



counties. The remaining columns report statistics for the individual coefficients ranging from their minimum to maximum values. One trait of the GWR results is that the median value across all 381 counties is usually quite similar to the standard regression results reported in column (3) of Table 1, though there are a few cases where there are some differences such as education.

Column (1) shows that the null hypothesis of 1995-2000 job growth coefficients being equal across PP counties cannot be rejected at any meaningful level of significance. This is consistent with the findings in Panels D-F of Table 2, which also suggested that there is little variation in responsiveness. Further evidence that greater economic opportunities have a fairly uniform response across all PP counties was uncovered when estimating the GWR model using the specification in column (4) of Table 1 that includes all of the labor-supply variables such as the employment/population rate (not shown). Specifically, with the exception of the male full-time employment share ( $p = .08$ ), the null hypothesis of no spatial differences could not be rejected at the 10 percent level for employment growth and the other labor-market variables.

The GWR median-county job growth response of  $-0.077$  is slightly greater in magnitude than what was reported with standard regression techniques in column (3) of Table 1. In further analysis, we split the GWR sample in a fashion corresponding to the split of PP and non-PP counties underlying the OLS estimates shown in Table 1. The *most* negative response for the 2647 non-PP counties was  $-0.047$  when using GWR (not shown), which is far less than the *least* negative response of  $-0.071$  for the PP counties. Together, these results suggest that there would be large antipoverty benefits from place-based economic development in PP counties, and that all would fairly equally benefit from growth.

In contrast to job growth, there are 12 other variables whose coefficients vary across PP counties based on the 15 percent significance level. While they are all not noteworthy, three cases of spatial variation in the coefficients warrant further attention due to their importance to place-based policy and in explaining the geographical heterogeneity of PP clusters.

The first of these is the coefficient for the average surrounding county poverty rate, which reflects the strength of the clustering/spillover effects from contiguous counties. A large response would suggest advantages to a broader-based economic development policy that may extend to

neighboring non-PP counties. As shown in Table 3, the average adjacent-county poverty rate coefficient varies from 0.041 to 0.189, almost a fivefold difference. Figure 2 shows that the weakest clustering/spillover effects occur in the Central Appalachia and the historic Southeast Cotton belt region. The strongest spillover effects from neighboring counties occur in the Western and Great Plains PP counties that have high shares of Hispanics and Native Americans. Thus, these counties could most benefit from broader-based regional programs that also reduce poverty in their neighbors.

The next variable with important spatial variation is the influence of the population share of female-headed families with children. Table 3 shows the coefficients varying from 0.286 to 0.774, while Figure 3 shows the spatial variation in the variable's effect. The most adverse poverty-increasing effects of having higher shares of single mothers with children are in the lower Mississippi Delta and along the heavily Hispanic Rio Grande. Thus, these counties would especially benefit from policies that provide work supports to single mothers such as more flexible childcare, better transportation, and training. Conversely, the female-head coefficients are smaller in Central Appalachian and Southern Highlands PP counties, as well as for PP counties with high Native American population shares in the upper Great Plains region, which implies they have smaller potential payoffs from such work supports.

Another key variable is the population share between ages 18 and 24 because that cohort often lacks labor-market experience and human capital. Table 3 shows that this coefficient varies from 0.029 to 0.486 across PP counties. As shown in Figure 4, the largest adverse poverty-increasing response to a higher share of young adults occurs in the Southwestern and Great Plains PP counties, which tend to have high shares of recent immigrants or Native Americans. Thus, policies providing young adults with more employment opportunities, or identifying suitable employment elsewhere, would appear to have larger payoffs in these regions. Conversely, the 18 to 24 year old age share has a smaller impact in the Southeastern Cotton belt PP counties, as well as in the Southern Highlands and Central Appalachia. One possible reason is young adults have tended to flee these counties for better opportunities elsewhere (see Glasmeier and Farrigan, 2003 for Appalachia), which also reduces the labor-supply pressures that could

harm their remaining counterparts.

## 5. Conclusion

Economists have long debated the relative merits of antipoverty programs that help people versus those that help their “places.” This debate particularly applies to 381 persistent poverty (PP) counties in the U.S. because the relative severity and persistence of their economic deprivation has commonalities with poverty traps found in developing nations. Descriptive statistics show that PP counties not only have populations with characteristics that place them at a higher poverty risk, they also generally have much weaker labor-market conditions on average. A variety of regression specifications, including the use of geographically weighted regression (GWR) analysis, were used to assess the issue of whether antipoverty policies should be targeted to people or place. If cultural, geographic, or institutional factors retard labor supply responses to increased labor demand, economic activity would have only a marginal impact in reducing poverty, suggesting that these counties are severe “poverty traps.”

Standard regression analysis over a variety of specifications revealed that weaker (stronger) labor-market conditions cause much larger increases (decreases) in poverty in PP counties than in non-PP counties. This finding applied even when accounting for industry composition and a full contingent of labor-market indicators. Moreover, further assessment indicated that employment growth was more strongly related to the share of the population living below one-half of the poverty line in PP counties, which is particularly encouraging given that this group has the most severe person-based impediments. The GWR results further confirmed that employment growth has a much stronger impact in PP counties. For example, the favorable poverty reducing impacts of job growth was about one-half again larger in the PP-county with the *smallest* job-growth poverty response compared to the *largest* job-growth poverty response in the other 2647 non-PP counties. The GWR results also suggested that job growth has relatively uniform impacts across all PP counties, indicating that economic development does not need to be targeted to particular PP county clusters.

The standard regression results also indicated that PP county poverty rates are not more sluggish in adjusting to economic events than the remaining counties, and there does not appear

to be greater clustering or spillover responses to neighboring county poverty. This further suggests that PP counties may be pulled out of poverty under more favorable conditions.

While the GWR analysis did not reveal spatial variation in the poverty effects of job growth across PP counties, about one-half of the variable regression coefficients had statistically significant geographical variation. For example, the GWR approach identified that the female-headed families with children share had its most adverse impacts along the Rio Grande and in the lower Mississippi Delta region, where the 18-24 year old age share had its most adverse impacts in western PP counties. Thus, policies aimed to provide place-based supports may need to target these demographic attributes in those regions. Generally, the GWR approach appears efficacious in identifying the spatial richness of the causal mechanism underlying poverty, which may not be easily brought to light with the global averages from standard regression approaches. Therefore, we see GWR as being well suited to inform policy on a larger-scale geographic basis.

In summary, these findings suggest that American PP counties are not hopeless poverty traps and that their deprivation can be reduced with more economic opportunities. Thus, place-based economic development policies should be considered as another poverty-fighting tool in conjunction with person-based policies in the most challenging regions. This is especially true in the work-first environment that currently underlies American welfare policies. Indeed, because a fundamental notion of the 1996 federal welfare reform was that states and localities should be given more discretion, such issues are increasingly important to states and localities. Thus, the next logical research step is to determine both the likelihood that economic development policies can create jobs in PP clusters, and what the best approaches are to implementing these policies. It may be that the geographic component of some counties induces a high poverty outcome through weak employment conditions, rather than through an inability to benefit from job growth. However, these answers likely vary across clusters, so a strong geographical dimension to this research would be required.

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**Table 1. Descriptive Statistics and Regression Results<sup>a</sup>**

Group	(1) Persistent Poverty Counties	(2) Non Persist. Cty Poverty Counties	(3) 1999 Persist. Pov. Counties	(4) 1999 Persist. Pov. Counties	(5) 1999 Non Persist. Pov. Counties	(6) 1999 Non Persist. Pov. Counties
1999 Poverty Rate	26.3 (5.5)	12.4 (4.3)	na	na	na	na
Lagged 1989 Poverty Rate	31.3 (7.3)	14.6 (5.3)	0.40 (10.41)	0.25 (7.45)	0.44 (24.29)	0.33 (19.98)
1989 Surrounding Cty Average Poverty	26.6 (6.6)	15.3 (4.9)	0.11 (3.35)	0.05 (1.54)	0.09 (6.26)	0.06 (4.44)
%1995-00 Emp Growth	4.9 (8.9)	9.8 (10.1)	-0.066 (3.85)	-0.031 (2.11)	-0.024 (5.34)	-0.010 (2.31)
1995-00 Structural Change <sup>b</sup>	0.069 (0.03)	0.056 (0.028)	14.1 (2.24)	10.7 (1.90)	6.8 (3.35)	5.3 (2.90)
Pop.x Structural Change	2378.2 (7467)	4104.9 (10462)	-2.6e-4 (1.23)	-2.7e-4 (1.60)	-2.0e-5 (2.20)	-1.9e-5 (2.57)
%Male Employment/Population	53.5 (7.6)	64.9 (8.0)		-0.13 (3.20)		-0.01 (1.06)
%Female Employment/ Population	43.3 (5.2)	52.9 (6.3)		-0.23 (4.81)		-0.16 (9.44)
%Civilian Male Unemployment Rate	8.7 (4.0)	5.3 (2.4)		0.03 (0.47)		0.14 (5.45)
%Civilian Female Unemployment Rate	9.3 (3.3)	5.2 (2.2)		-0.07 (1.12)		-0.02 (0.59)
% of Fulltime Employ. Males	86.5 (3.6)	86.2 (3.0)		-0.10 (1.33)		-0.08 (3.72)
% of Fulltime Employ. Females	74.2 (5.3)	69.4 (6.0)		-0.08 (1.76)		8.5e-4 (0.06)
% employed residents in Agric., forestry or fisheries	7.1 (5.7)	7.6 (6.9)		0.18 (2.09)		0.20 (9.36)
% employed residents in Goods	25.9 (8.8)	25.3 (9.2)		0.04 (0.48)		0.05 (3.40)
Other Industry Shares <sup>c</sup>			N	Y	N	Y
1995-2000 Residence Mobility <sup>d</sup>			N	Y	N	Y
County Population	19,925 (16,723)	26,399 (25,013)	1.3e-05 (1.16)	1.3e-05 (1.48)	5.3e-07 (2.12)	4.7e-07 (2.44)
Cty Pop x Nonmetro Cnty Indic			-1.3e-05 (1.10)	-8.6e-06 (0.96)	-1.5e-06 (0.85)	-6.3 (0.36)
% Population that immigrated between 1995-2000	0.7 (1.2)	1.0 (1.3)	0.27 (0.98)	0.43 (1.75)	0.53 (5.51)	0.43 (4.77)
% Population that immigrated between 1990-1994	0.5 (1.1)	0.6 (0.9)	0.49 (1.52)	0.38 (1.04)	-0.30 (2.17)	-0.25 (1.97)
%Not HS Graduate (age ≥ 25yrs)	34.8 (7.6)	20.9 (7.4)				
%HS Graduate (age ≥ 25yrs)	32.9 (5.2)	35.1 (6.6)	-0.21 (3.56)	-0.10 (2.02)	-0.15 (8.73)	-0.10 (6.39)
%Some College, no degree (age ≥ 25yrs)	16.5 (3.5)	21.0 (4.2)	-0.10 (1.25)	-0.08 (1.11)	-0.08 (3.79)	-0.08 (4.21)
%Associate College Degree (age ≥ 25yrs)	4.0 (1.7)	6.0 (1.9)	-0.45 (3.00)	-0.36 (2.84)	-0.19 (5.77)	-0.14 (4.54)
%Bachelors Degree or more (age ≥ 25yrs)	11.8 (5.1)	17.1 (7.7)	-0.07 (1.31)	0.07 (1.14)	-0.12 (9.49)	-0.06 (3.75)
% of HHs female-headed with children	9.2 (3.3)	5.7 (1.8)	0.63 (5.70)	0.68 (5.56)	0.44 (9.06)	0.56 (10.47)
% of HHs male-headed with children	2.2 (0.9)	2.1 (0.6)	0.34 (1.57)	0.50 (2.63)	0.16 (1.72)	0.20 (2.43)

%Pop African American	25.3 (24.2)	6.4 (10.5)	-0.06 (2.99)	-0.07 (3.56)	-0.01 (1.69)	-0.02 (2.67)
%Pop Other Race (non Caucasian, Black)	9.7 (16.3)	5.9 (6.7)	-0.02 (0.88)	-0.04 (1.41)	0.02 (0.94)	0.005 (0.35)
%Pop Hispanic	10.4 (22.6)	5.5 (9.5)	-0.03 (2.11)	-0.04 (2.51)	-0.02 (2.20)	-0.03 (2.63)
%Metropolitan Area County <sup>c</sup>	6.6 (24.8)	30.2 (45.9)	Y <sup>e</sup>	Y <sup>e</sup>	Y <sup>e</sup>	Y <sup>e</sup>
Age Shares <sup>f</sup>			Y	Y	Y	Y
State Indicators			Y	Y	Y	Y
R <sup>2</sup>			0.848	0.899	0.867	0.895
N	381	2647	381	381	2647	2647

a. In parentheses in columns (1) and (2) are standard deviations and in columns (3)-(6) are the absolute values of the robust t-statistics. For the empirical analysis, a persistent poverty county is defined as having a poverty rate greater than 20% in each of 1979, 1989, and 1999, which includes a few more counties than other definitions described above. 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.

b. The structural change index is the share of the county's employment that would have to change sectors in each year 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. Other industry shares include percent of employed residents in transportation and public utilities; trade and entertainment; information; finance and real estate; services; with public administration as the omitted sector.

d. For 2000, the mobility measures are percent of residents who lived in the same house in 1995; percent of residents who lived in the same county but a different house in 1995; and for metropolitan area residents, the percent of residents who lived in the same metropolitan area in 1995 but different house.

e. Several specific metropolitan county type variables are in the regression model: 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.

f. 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 of Persistent/non-Persistent Poverty Regressions<sup>a,b</sup>**

	(1) 1999 Persist. Pov. Counties	(2) 1999 Non-Persist. Pov. Counties
<b>A. Dep Var is % of Population &lt;50% Poverty Line</b>		
Lagged 1989 Poverty Rate < 50% of Poverty Line	0.33 (8.97)	0.34 (15.45)
1989 Surrounding Cty Avg Poverty	0.06 (2.19)	0.04 (5.05)
%1995-00 Emp Growth	-0.023 (2.19)	-0.007 (2.74)
R-squared	.78	.76
<b>B. Dep Var is % of Population 50-100% Poverty Line</b>		
Lagged 1989 Poverty Rate between 50-100% Poverty Line	0.29 (7.17)	0.33 (16.70)
1989 Surrounding Cty Avg Poverty	0.09 (3.60)	0.09 (8.93)
%1995-00 Emp Growth	-0.035 (2.86)	-0.015 (4.80)
R-squared	.74	.81
<b>C. Dep Var is % of Population 100-150% Poverty Line</b>		
Lagged 1989 Poverty Rate between 100-150% Poverty Line	0.21 (3.48)	0.34 (18.92)
1989 Surrounding Cty Avg Poverty	0.03 (1.08)	0.08 (7.74)
%1995-00 Emp Growth	0.004 (0.33)	-0.012 (3.66)
R-squared	.49	.80
<b>Base Model Dep Var is % of Pop &lt; Poverty Line:</b>		
<b>D. High 1990 Primary and Manufacturing Shares X 1995-00 Employment Growth<sup>c</sup></b>		
F-statistic for high primary- and high manufacturing-employment X employment growth interactions.	0.36 (p=.700)	0.60 (p=.548)
<b>E. High 1990 female and male emp/pop rates X 1995-00 Employment Growth<sup>d</sup></b>		
F-statistic on the high emp/pop X employment growth interactions.	0.66 (p=.520)	0.08 (p=.928)
<b>F. Education attainment X 1995-00 Employment Growth</b>		
%High School x 1995-00 Employment Growth	NA	0.002 (1.59)
%Some College x 1995-00 Employment Growth	NA	-0.002 (1.52)
%Assoc. Degree x 1995-00 Employment Growth	NA	-0.004 (1.74)
%College Grad x 1995-00 Employment Growth	NA	0.002 (2.93)
%1995-00 Emp Growth	NA	-0.063 (0.89)
F-statistic on the education X emp. growth interactions.	0.13 (p=.973)	6.43 (p=.0000)

a. The models use the same explanatory variables as used in columns (3) and (5) of Table 1 except that Models A, B, and C substitute the appropriate lagged 1989 dependent variable. The full set of results is available on request to the authors. Unless indicated as a p-value, in parentheses are the robust t-statistics.

b. The individual regression components are reported in the sensitivity runs in Models D, E, and F only if the added interaction variables are jointly significant at the 5 percent level.

c. Two indicators were created for having an above average 1990 share in primary production (>11.7%) and in manufacturing (>19.5%), which are derived from the PP county sample averages. These indicators were then interacted with 1995-2000 employment growth and added to the base model.

d. Two indicators were created for having above average 1990 female and male employment/population rates (respectively >40.7%, >57.8%), which were derived from the PP county sample averages. These indicators were interacted with 1995-2000 employment growth and added to the base model.

**Table 3: Overview of the Persistent-Poverty County GWR Regression Coefficients<sup>a</sup>**

	p-value <sup>b</sup>	Minimum	Lwr Quartile	Median	Upr Quartile	Maximum
County Intercept	0.000 <sup>***</sup>	-8.717	0.608	9.140	12.873	14.896
Lagged 1989 Poverty Rate	0.13 <sup>#</sup>	0.391	0.422	0.448	0.462	0.475
1989 Surrounding Cty Average Poverty	0.02 <sup>*</sup>	0.041	0.048	0.063	0.085	0.189
%1995-00 Emp Growth	0.95	-0.087	-0.079	-0.077	-0.075	-0.071
1995-00 Structural Change	0.05 <sup>*</sup>	7.150	8.360	9.938	15.039	28.665
Pop.x Structural Change	0.23	-0.0005	-0.0002	-0.0002	-0.0001	-0.0001
Metro Area Pop. County Population	0.01 <sup>**</sup>	-1.0E-06	-1.0E-06	0.000	0.000	2.0E-06
Cty Pop x Nonmetro Cnty Indic	0.50	7.0e-06	8.0e-06	9.0e-06	1.1e-05	2.2e-05
% Population that immigrated between 1995-2000	0.45	-1.6e-05	-8.0e-06	-7.0e-06	-6.0e-06	-3.0e-06
% Population that immigrated between 1990-1994	0.28	-0.042	0.314	0.438	0.446	0.526
%HS Graduate (age≥ 25yrs)	0.24	0.185	0.252	0.307	0.501	0.896
%Some College, no degree (age≥ 25yrs)	0.65	-0.163	-0.145	-0.130	-0.117	-0.094
%Associate College Degree (age≥ 25yrs)	0.33	-0.210	-0.203	-0.193	-0.183	-0.065
%Bachelors Degree or more (age≥ 25yrs)	0.69	-0.346	-0.254	-0.227	-0.200	-0.180
% of HHs female-headed with children	0.25	-0.067	-0.013	0.009	0.021	0.059
% of HHs male-headed with children	0.04 <sup>*</sup>	0.286	0.563	0.610	0.631	0.774
%Pop African American	0.96	0.304	0.429	0.443	0.460	0.498
%Pop Other Race (non Caucasian, Black)	0.15 <sup>#</sup>	-0.085	-0.063	-0.057	-0.056	-0.053
%Pop Hispanic	0.55	-0.016	-0.004	0.005	0.010	0.019
%Pop Children<7 yrs old	0.01 <sup>**</sup>	-0.065	-0.037	-0.029	-0.022	-0.017
%Pop Children 7-17 yrs old	0.000 <sup>***</sup>	-0.502	-0.462	-0.378	-0.082	0.339
%Pop Adults 18 to 24 yrs old	0.72	0.267	0.292	0.316	0.362	0.405
%Pop Adults 60-64 yrs old	0.000 <sup>***</sup>	0.029	0.081	0.137	0.307	0.486
%Pop. over 65 yrs old	0.06 <sup>†</sup>	-0.223	0.025	0.149	0.286	0.595
	0.000 <sup>***</sup>	-0.048	-0.040	-0.008	0.155	0.326
N	381					
Local sample size or bandwidth <sup>c</sup>	371					
R <sup>2</sup> GWR model	0.847					
R <sup>2</sup> OLS model	0.816					
F-statistic of geographic variation in model <sup>d</sup>	3.7918					
	p=5.3E-07 <sup>***</sup>					

a. See the notes to Table 1 for variable definitions.

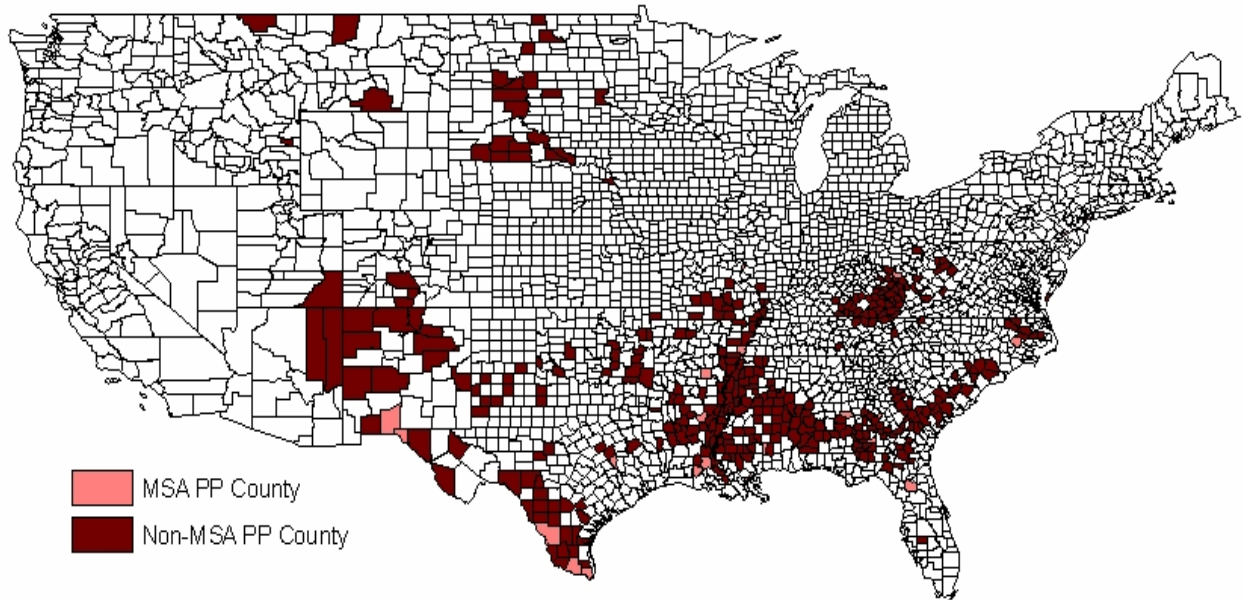
b. The significance of the null hypothesis that the regression coefficient does not vary across all PP counties.

c. This represents the bandwidth or the local number of PP counties used in the estimation of each county's individual regression coefficients (i.e., number of "neighbors"). See Fotheringham et al. (2002) for details.

d. F-statistic of the null hypothesis that adding spatial variation to the regression coefficients does not improve the fit of the model.

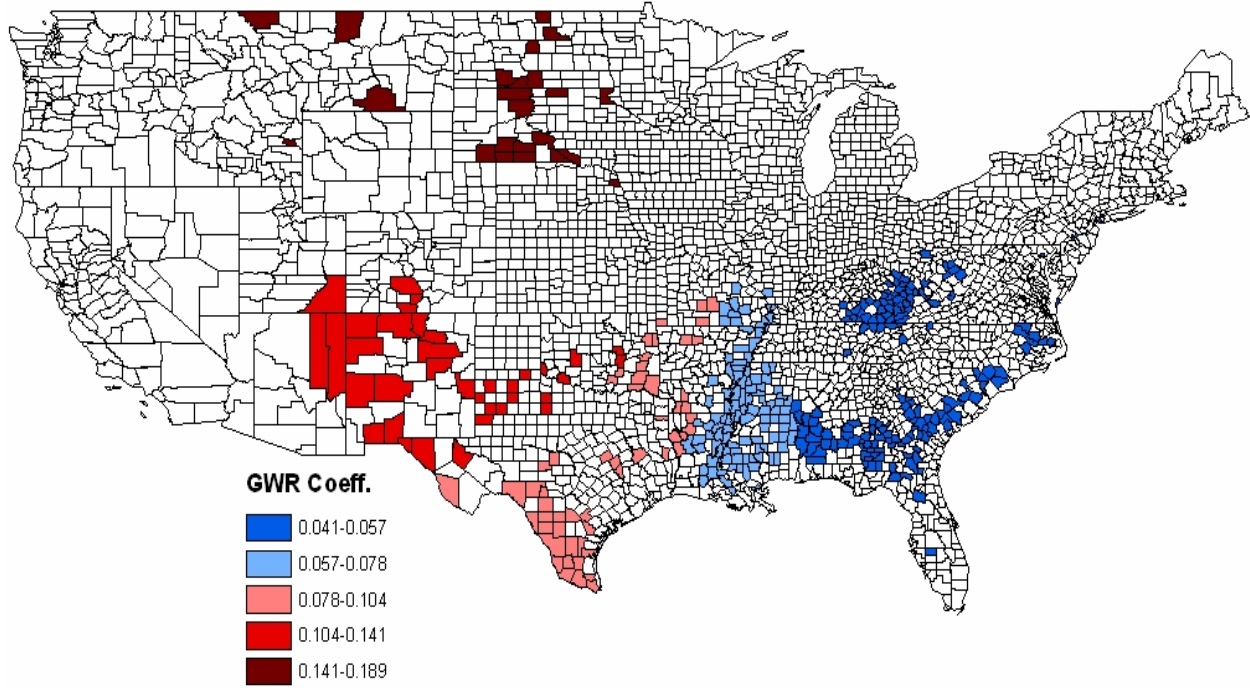
Significance levels: \*\*\* 0.1% level; \*\* 1% level; \* 5% level; † 10% level; # 15% level

**Figure 1: 1999 Persistent Poverty Counties: 1979-1999 Definition**

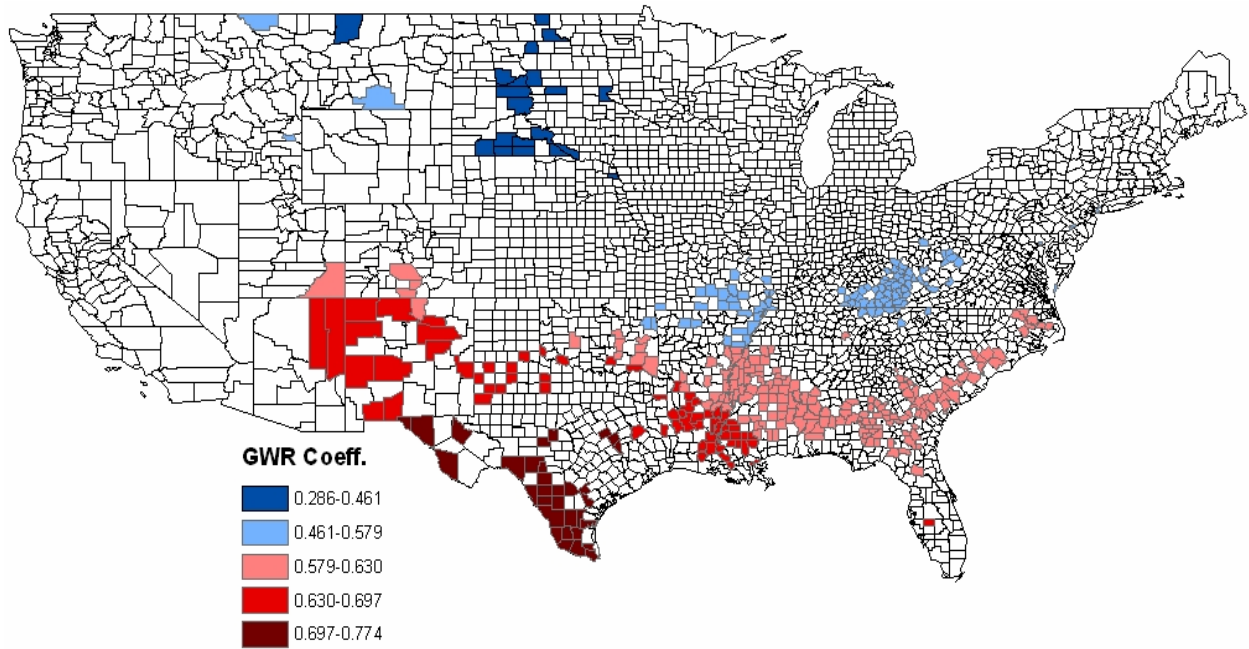


Note: The highlighted counties are persistent-poverty counties with 20 percent or more residents that were poor in each of the 1980, 1990, and 2000 censuses (i.e., measured for 1979, 1989, and 1999).

**Figure 2: GWR Variation in the Average Surrounding County Regression Coefficient.**



**Figure 3: GWR Variation in the Female-Headed Family with Children Regression Coefficient.**



**Figure 4: GWR Variation in the Share of 18-24 Years of Age Regression Coefficient.**

