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Persistent Pockets of Extreme American Poverty and Job Growth: Is There a Place-Based Policy Role?

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Over the past four decades almost 400 U.S. counties have persistently experienced poverty rates in excess of 20%. This raises the question of whether poverty-reducing policies should be directed more at helping people or helping the places where they reside. Using a variety of approaches, including geographically weighted regression analysis, we find that local job growth especially reduces poverty in persistent-poverty counties. Findings also show these counties do not respond more sluggishly to exogenous shocks. Finally, this analysis identifies some key geographic differences among persistent-poverty clusters. Taken together, place-based economic development has a potential role for reducing poverty in these counties.

Key words: economic development, geographically weighted regression, persistent poverty, place-based policies, poverty

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 2004 U.S. Census Bureau poverty rate of 12.7% exceeded that registered in 1973 (11.1%).[1] The poverty rate during the intervening three decades also has regularly been above 12.7%. More discouraging is that significant clusters of severe poverty continue to exist 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% in 1999.

It is especially troublesome that most of these counties have persistently experienced high rates of poverty: 382 counties had poverty rates exceeding 20% in each of 1959, 1969, 1979, 1989, and 1999 (Miller and Weber, 2004). 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

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[1] For more details of the dating of U.S. business cycles, see the National Bureau of Economic Research at 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.

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 rarely been empirically explored [Partridge and Rickman (2005) is an exception]. 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 nature and small scale of most persistently high poverty counties raise the issue of whether they can sustain significant economic activity. Also, job growth may have fewer antipoverty benefits in remote rural areas because of low levels of education, lack of formal childcare, and transportation constraints (Davis, Connolly, and Weber, 2003). Therefore, despite the attention given to poverty clusters in developing economies (e.g., Ravallion and Woden, 1999; Lucas, 2001), there is surprisingly little research on whether there is a role for place-based economic development policy in persistent pockets of American poverty. The answer would address whether antipoverty policies should focus primarily on directly helping *people*, or also on improving conditions in their *place* of residence.

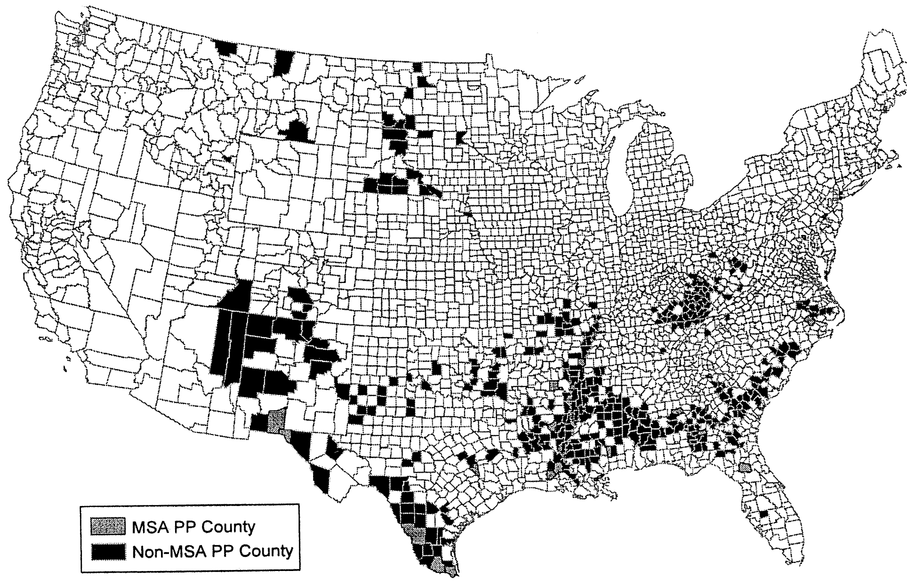
To that end, this study examines poverty rate determinants using Census 2000 data for the approximately 3,000 U.S. counties. We first focus on differences between counties with persistently high poverty (PP) and remaining counties to examine if economic conditions have a stronger antipoverty impact in PP counties. If so, this would support those who argue that place-based economic policies are needed components of anti-poverty 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 persistent poverty clusters.

The section below outlines the literature on place- and people-based antipoverty policy. The next section describes the empirical model and data, followed by a presentation and discussion of the results. The paper concludes with a summary of the findings and their policy implications.

Place-Based and People-Based Policy

We define a persistent high poverty county as having a poverty rate greater than 20% in each of 1979, 1989, and 1999, which includes a few more counties than more restrictive definitions (e.g., Miller and Weber, 2004; USDA, 2004). Figure 1 displays the persistent poverty counties, in which the four ethno-clusters described in the introduction are apparent. Almost all PP counties are nonmetropolitan and generally located far from large urban centers. Thus, it is not a priori clear whether antipoverty policies should be solely people-based or should also include place-based components.

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). Hence, it is not surprising economists often contend that policies oriented toward *place*, such as subsidies and tax breaks aimed at distressed communities, are wasteful. They argue that place-based policies create a culture of dependency which dampens incentives, including those that would induce the disadvantaged to relocate to better job opportunities (Glaeser, 1998). Although there may be



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

Figure 1. 1999 persistent poverty counties: 1979–1999 definition

willing residents in a poor community to draw upon to fill new jobs, 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 to the intended beneficiaries (Peters and Fisher, 2002). These critics instead generally prefer only person-based policies such as education and training, job counseling, and relocation assistance targeted to individuals.

Place-based policies are also questionable if the poverty clusters are too remote or small such that "backwash" effects of economic activity being drawn into urban centers inhibit economic development (Barkley, Henry, and Bao, 1997; Henry, Barkley, and Bao, 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 (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).

However, those advocating place-based approaches tend to argue that people and place-based policy play a complementary role. Arguing for a supporting place-based targeting approach are several factors which limit labor mobility between PP and lower-poverty counties. Foremost, workers with less human capital are not as geographically mobile (Yankow, 2003), though Nord (1998) finds some evidence that "poor" working-age migration rates are similar to the corresponding rates for the "non-poor." Also, 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 these areas are where low-skilled workers may be most in demand (Lucas, 2001). Consequently, solely relying on people-based policies may be inadequate in addressing spatial concentrations of poverty (Blank, 2005).

With limited labor mobility, employment growth in PP counties could significantly reduce poverty. 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. This leaves more of the benefits for the intended disadvantaged beneficiaries, consistent with arguments for place-based policies. Thus, although in some ways remoteness or small scale might be a drawback, it may have the advantage that long-term residents garner more of the benefits of job growth. In the typical case, Bartik (1993) estimates 60%–90% of new jobs are eventually taken by migrants in the long run, with Partridge and Rickman (2006a) reporting similar estimates. This suggests many original residents can benefit from employment growth in the long run, including many disadvantaged original residents who would be more likely to have initially not been employed.[2]

Place-based policies also derive their appeal from the notion that wide spatial variation in local attributes thwarts "one-size-fits-all" policies. Place and related contextual effects influence economic vitality and shape the character of the people (Blank, 2005). In isolated inner cities and remote rural areas, many of the disadvantaged have less access to job training, counseling, healthcare, childcare, and transportation, suggesting government-service delivery should reflect these spatial differences (Allard, Tolman, and Rosen, 2003). Even in instances where person-based approaches may be appropriate, advocates of place-based policies argue they have an important complementary role (Blank, 2005). 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 further argue that economic development policies can effectively enhance local growth because of factors such as neighborhood effects, economic role models, and knowledge spillovers. 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 which would merit targeting (Ravallion and Wodon, 1999). Finally, there may be more widespread voter support for targeting disadvantaged locations than disadvantaged people.

The long duration and spatial concentration of persistent poverty counties provide a good empirical test of whether place-based policies designed to improve job growth can reduce poverty. Yet because residents of PP locales typically possess attributes that place them at higher risk of poverty (i.e., people-based problems), it is possible locally created jobs will instead be filled by more qualified workers who are: (*a*) existing residents already above the poverty line, (*b*) new migrants, or (*c*) new commuters. To examine this empirical issue, we explore whether ceteris paribus increases in job growth have different poverty-reducing effects in PP counties, in which greater or equal impacts would be supportive of using geographically targeted economic development policies.

[2] Blanchard and Katz (1992) conclude migrants take all the newly created jobs in the long run, but this follows implicitly from the long-run assumptions of their model [see Partridge and Rickman (2006a) for discussion].

Empirical Model

The empirical model generally follows specifications used in past spatial studies of overall poverty rates, such as Madden (1996); Levernier, Partridge, and Rickman (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 to changes in socioeconomic conditions are sluggish, making them 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 also can change the expected poverty rate. It may take time though 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 which determine the expected poverty rate, and the lagged poverty rate to account for disequilibrium adjustment. A significant coefficient for the lagged poverty variable suggests the existence of sluggish disequilibrium adjustment of poverty rates to socioeconomic shocks, making poverty rates autoregressive. An insignificant coefficient suggests a more rapid adjustment process, and an absence of autoregressiveness in poverty rates. Another advantage of controlling for the lagged poverty rate is that it also helps control for any "fixed effects" which persistently lead to a high or low county poverty rate, ceteris paribus.

Table 1 lists the variables used in the empirical model and the notes describe their sources. The dependent variable is the overall 1999 county person poverty rate. The causal variables are generally self-explanatory, in which most of our attention will be on the role of job growth, as well as the lag of the own-poverty rate and average surrounding-county poverty rate to assess the effects of persistence and clustering/ spillovers. The values of the base model's explanatory variables are measured around the year 2000 (to use the 2000 Census), with the exceptions being the lagged 1989 poverty rate variables. An alternative specification lags the explanatory variables an additional 10 years to about 1990 (to use the 1990 Census) with exceptions being the 1995–2000 employment growth and the lagged 1989 poverty measures, which are used in all models. The following is the base empirical model that is estimated separately for PP counties and for non-persistent poverty counties (county i in state s):

$$(1) \qquad POV_{is1999} = \alpha POV_{is1989} + \theta AVGNEIGHBORPOV_{is1989} + \boldsymbol{\varphi}\mathbf{ECON}_{is} + \boldsymbol{\beta}\mathbf{CTY\_TYPE}_{is} + \boldsymbol{\gamma}\mathbf{DEMOG}_{is} + \sigma_s + \varepsilon_{is}.$$

For the explanatory factors, *AVGNEIGHBORPOV* is the average 1989 poverty rate in contiguous counties (consists of all neighbors including any PP and/or non-PP counties), which picks up spillover/clustering effects. The **ECON** vector contains employment growth and measures of industry restructuring.[3] Employment growth is included because we

[3] 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.

Table 1. 1999–2000 Descriptive Statistics and Regression Results

Variable	[1] 1999–2000 PP Counties	[2] 1999–2000 Non-PP Counties	[3] OLS PP Counties	[4] 2SLS PP Counties	[5] OLS Non-PP Counties	[6] 2SLS Non-PP 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)	0.48 (9.79)	0.44 (24.29)	0.49 (22.05)
1989 Surrounding County Average Poverty	26.6 (6.6)	15.3 (4.9)	0.11 (3.35)	0.07 (1.99)	0.09 (6.26)	0.08 (4.44)
% 1995–2000 Employment Growth	4.9 (8.9)	9.8 (10.1)	-0.066 (3.85)	-0.150 (4.94)	-0.024 (5.34)	-0.110 (5.46)
1995–2000 Structural Change [a] [*1985–1990*]	0.069 (0.03)	0.056 (0.028)	14.1 (2.24)	5.0 (0.67)	6.8 (3.35)	-2.5 (1.37)
2000 Pop. × 1995–2000 Structural Change [*1990* × *1985–90*]	2,378.2 (7,467)	4,104.9 (10,462)	-2.6e-4 (1.23)	1.7e-4 (1.27)	-2.0e-5 (2.20)	2.7e-6 (0.24)
2000 % Male Employment/Pop. [b]	53.5 (7.6)	64.9 (8.0)				
2000 % Female Employment/Pop.	43.3 (5.2)	52.9 (6.3)				
2000 % Civilian Male Unemploy.	8.7 (4.0)	5.3 (2.4)				
2000 % Civilian Female Unemploy.	9.3 (3.3)	5.2 (2.2)				
2000 % Full-Time Employ. Males	86.5 (3.6)	86.2 (3.0)				
2000 % Full-Time Employ. Females	74.2 (5.3)	69.4 (6.0)				
2000 County Population [*1990*]	19,925 (16,723)	26,399 (25,013)	1.3e-05 (1.16)	-1.5e-05 (1.59)	5.3e-07 (2.12)	-2.5e-07 (0.57)
2000 County Pop. × Nonmetro County [*1990*]			-1.3e-05 (1.10)	-1.5e-05 (1.09)	-1.5e-06 (0.85)	-1.3e-06 (0.52)
% Pop. that Immigrated between 1995–2000 [*1985–1990*]	0.7 (1.2)	1.0 (1.3)	0.27 (0.98)	1.16 (2.55)	0.53 (5.51)	0.18 (1.29)
% Pop. that Immigrated between 1990–1994 [*1980–1984*]	0.5 (1.1)	0.6 (0.9)	0.49 (1.52)	-0.23 (0.50)	-0.30 (2.17)	0.12 (0.63)
2000 % Not HS Graduate (age ≥ 25 yrs.) [*1990*]	34.8 (7.6)	20.9 (7.4)				
2000 % HS Graduate (age ≥ 25 yrs.) [*1990*]	32.9 (5.2)	35.1 (6.6)	-0.21 (3.56)	-0.13 (2.24)	-0.15 (8.73)	-0.09 (5.21)
2000 % Some College, No Degree (age ≥ 25 yrs.) [*1990*]	16.5 (3.5)	21.0 (4.2)	-0.10 (1.25)	-0.08 (0.86)	-0.08 (3.79)	0.01 (0.51)
2000 % Associate Degree (age ≥ 25 yrs.) [*1990*]	4.0 (1.7)	6.0 (1.9)	-0.45 (3.00)	0.004 (0.02)	-0.19 (5.77)	-0.10 (2.68)
2000 % Bachelor's Degree or more (age ≥ 25 yrs.) [*1990*]	11.8 (5.1)	17.1 (7.7)	-0.07 (1.31)	0.13 (1.84)	-0.12 (9.49)	-0.05 (3.48)
2000 % of Hsholds. Female-Headed w/Children [*1990*]	9.2 (3.3)	5.7 (1.8)	0.63 (5.70)	0.13 (0.98)	0.44 (9.06)	0.12 (2.15)
2000 % of Hsholds Male-Headed w/Children [*1990*]	2.2 (0.9)	2.1 (0.6)	0.34 (1.57)	-0.09 (0.31)	0.16 (1.72)	0.07 (0.63)
2000 % Pop. African-American [*1990*]	25.3 (24.2)	6.4 (10.5)	-0.06 (2.99)	-0.01 (0.48)	-0.01 (1.69)	0.004 (0.45)
2000 % Pop. Other Race (non-Caucasian, Black) [*1990*]	9.7 (16.3)	5.9 (6.7)	-0.02 (0.88)	0.01 (0.48)	0.02 (0.94)	0.03 (1.50)

(continued . . .)

Table 1. Continued

Variable	[1] 1999–2000 PP Counties	[2] 1999–2000 Non-PP Counties	[3] OLS PP Counties	[4] 2SLS PP Counties	[5] OLS Non-PP Counties	[6] 2SLS Non-PP Counties
2000 % Pop. Hispanic	10.4	5.5	-0.03	-0.02	-0.02	-0.02
[*1990*]	(22.6)	(9.5)	(2.11)	(0.80)	(2.20)	(1.63)
2000 Industry Shares [c]			N	N	N	N
1995–2000 Residence Mobility [d]			N	N	N	N
% Metropolitan Area County [e]	6.6	30.2	Y	Y	Y	Y
	(24.8)	(45.9)				
2000 Age Shares [f]			Y	Y	Y	Y
[*1990*]						
State Indicators			Y	Y	Y	Y
R^2			0.848	0.804	0.867	0.813
No. of Counties	381	2,647	381	381	2,647	2,647

Notes: Values in parentheses in columns [1] and [2] are standard deviations, and in columns [3]–[6] are the absolute values of the robust t-statistics. In columns [1], [2], [3], and [5], all of the variables are measured at the indicated year circa 2000. The models in columns [4] and [6] also treat 1995–2000 employment growth as endogenous. In columns [4] and [6], with the exception of 1995–2000 job growth, 1989 average surrounding county poverty rate, and 1989 lagged own-county poverty rate, the other variables are lagged an additional 10 years to circa 1990 (as shown in bracketed italics in the second row of the variable entry). 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 (2006b) for more details of variables and sample construction.

[a] The structural change index is the share of the county's employment that would have to change sectors in 1995 [*1985*] and 2000 [*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.

[b] Descriptive statistics are provided for the employment rate, unemployment rate, and full-time employment status, by gender, because they are used in sensitivity analysis for which results are not shown in the table.

[c] The 2000 industry shares include percentage of employed residents in agriculture; goods producing; transportation and public utilities; trade and entertainment; information; finance and real estate; and services—with public administration as the omitted sector.

[d] For 2000, the mobility measures are percentage of residents who lived in the same house in 1995; percentage of residents who lived in the same county but a different house in 1995; and for metropolitan area residents, the percentage of residents who lived in the same metropolitan area in 1995 but a 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 percentage of the population less than 7 years old, between 7–17, 18–24, 60–64, and 65 and over. The omitted category is the percentage between 25–59 years of age.

are primarily interested in the effects of economic development, which is generally perceived to be employment growth by policy makers (Bartik, 2001). Including other economic measures such as the unemployment rate blurs the effects of economic growth, while also introducing multicollinearity. To be sure, in contrast to national studies, employment growth is routinely included in regional poverty studies because it is perceived to better reflect increased labor demand than other labor market indicators (Partridge and Rickman, 2006b, pp. 83–84). Moreover, Partridge and Rickman (2003) demonstrate that regional employment and population shifts reflect regional utility differentials, in which they argue increased regional utility should be the goal of economic development. Employment growth can reduce poverty by reducing unemployment, increasing labor force participation, increasing the share of full-time jobs, moving people up the occupational ladder, and increasing wage rates. We consider the effects of some of these other economic measures in sensitivity analysis to help trace how employment growth reduces poverty.

Industry restructuring is measured as the share of employment that has shifted across sectors over the recent period. More restructuring is expected to increase poverty through job dislocation and problems associated with obtaining comparable reemployment status. We also interact the restructuring variable with population to see if it is associated with better job matching, and less adverse poverty effects of restructuring.

The **CTY_TYPE** vector incorporates county type (e.g., whether the county is suburban, contains a central city, or is nonmetropolitan) and population measures. One potential control variable is county cost of living, which is not available. One possible proxy could be average rental values, 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 (and cost of living) by including county and metropolitan population and state fixed effects which account for amenity differentials.[4]

The **DEMOG** vector includes demographic traits of the population commonly believed to be potentially correlated with poverty outcomes such as racial composition, average educational attainment, recent immigration status, single-headed household status, and age (Levernier, Partridge, and Rickman, 2000). The educational attainment variables are the population proportions who have completed high school, completed some college but have no degree, have only an associate college degree, or have a bachelor's degree or higher. Because of its positive association 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 lesser job skills, and there is only one income earner in the household (Levernier, Partridge, and Rickman, 2000). To the extent recent immigrants have higher poverty and compete with low-skilled natives (Borjas, 2003), a higher share of recent immigrants would be expected to increase the poverty rate.

In equation (1), 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 consider whether spatial clustering of the residuals is affecting the reported *t*-statistics. 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-state effects are subsumed into the state fixed effects.

If place-based factors influence poverty rates, it would be reasonable to assume 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 and low high school completion rates.

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[4] For example, Gyourko and Tracy (1989) found that a strong proxy for a cost-of-living index was simply derived from log population and location in the four Census divisions. In our case, simply regressing the 2000 median county rent on the variables in the **CTY_TYPE** vector and state fixed effects yielded an R^2 of 0.733, indicating we are already including the key underlying exogenous contributors to cost-of-living differentials.

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.[5]

Poverty-generating processes also may differ by geography. For example, some clusters are more remote from large urban centers. Remoteness may be associated with lower rates of gross migration and commuting flows, which may cause poverty responses to socioeconomic shocks to differ from those of less remote areas. 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, Brunsdon, and Charlton (2002).

The GWR approach weights the explanatory variables in "neighboring" counties to produce spatially distinct regression coefficients for each observation (Fotheringham, Brunsdon, and Charlton, 2002).[6] 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) (Fotheringham, Brunsdon, and Charlton). The GWR process can be represented for county i in state s situated in location g as:

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

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:

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

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 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.

Besides capturing spatial heterogeneities in the regression coefficients, GWR has other advantages. 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 (i.e., such "omitted" effects are part of the constant). 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 may more readily address spatial heterogeneity than global spatial-econometric approaches that account for spatial error dependence (Fotheringham, Brunsdon, and Charlton, 2002, p. 242). For example, spatial correlation in the

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[5] For example, Blacks generally have a lower propensity to migrate (Spilimbergo and Ubeda, 2004), there appear to be differences in the propensity to form ethnic enclaves among Hispanics (Stoll, 1999), and there are differing institutional arrangements on Native American reservations (Leichenko, 2003).

[6] The GWR approach is a subset of local-weighted regression techniques. Another example of a GWR/local-weighted regression study is McMillen's (2003a) examination of Chicago neighborhood home sales.

error terms could reflect high spatial correlation in the explanatory variables and heterogeneity in the corresponding regression coefficients. The county-specific GWR regression coefficients address this particular heterogeneity problem (see footnote 18).

Empirical Results

The descriptive statistics in columns [1] and [2] of table 1 reveal that PP counties are at great disadvantage. In terms of disadvantage by place, they had about one-half the average 1995–2000 job growth of other counties, more structural change, average employment-population rates about 10 percentage points lower, and average unemployment rates about 4 percentage points higher. Consistent with clustering effects, PP counties are surrounded by counties whose lagged average poverty rate was over 11 percentage points higher. High poverty in these counties also could simply reflect person-based demographic traits typically associated with higher poverty. They had nearly twice the adult population share who 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 accounting for these demographic attributes.

Base Case Results

Columns [3]–[4] report the regression results for PP counties, and columns [5]–[6] show the corresponding results for the sample of non-PP counties. The base models are reported in columns [3] and [5], in which a Chow test indicated the PP and non-PP samples are governed by different data-generating processes.[7] As described below, the other columns report the results of using instrumental variables for five-year employment growth and using lagged predetermined demographic variables to assess the potential role of endogeneity.

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 they both undergo a somewhat sluggish adjustment to exogenous shocks.[8] 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 rather than their responses to shocks.

The positive coefficient on the lagged average surrounding county poverty rate variable suggests, ceteris paribus, counties that are surrounded by high-poverty counties have higher poverty, while counties surrounded by lower-poverty counties have lower poverty. A one-percentage point higher average surrounding-county poverty rate is respectively associated with 0.11 and 0.09 higher own-county poverty rates for PP and non-PP counties. Therefore, although PP counties suffer from being surrounded by counties with higher poverty rates—because they are typically found in clusters—the relative responsiveness to neighboring county poverty is about the same across both samples.

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[7] 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 ($\chi^2_{[58]} = 471.8$, $p = 0.0000$).

[8] 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)).

For every one-percentage point increase in the five-year job growth rate (or about 0.2% more per year), the results also suggest the poverty rate falls an average of 0.066 points in PP counties, or almost threefold more than non-PP counties. This difference is significant at the 1% level based on a one-tailed test, which is notable given the myriad of demographic (person-based) factors included in the model.[9] The results are consistent with studies that find a larger poverty-reducing effect for high poverty rural areas in general (Crandall and Weber, 2004; Partridge and Rickman, 2005). The difference across samples in this study in the relationship 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.[10] Conversely, the general similarity of demographic results between the two samples suggests person-based effects generally have similar causal mechanisms.[11,12]

One concern is that poverty in PP counties is so severe it would begin to reduce productivity and job growth.[13] Endogeneity would negatively bias the PP employment growth coefficient. We tested this possibility with a Hausman test, but the test was insignificant at the 5% level, suggesting endogeneity is not a major concern.[14] Yet, ignoring the Hausman test and reestimating the base models in columns [3] and [5] using two-stage least squares (2SLS) actually strengthened our results. Specifically, illustrating that this potential negative bias may not be severe, the 2SLS coefficients became *more* negative, in which the PP county employment growth coefficient equaled -0.12 (t = 3.71) and the non-PP coefficient equaled -0.05 (t = 3.16).

In the base specifications, we control for contemporaneous values of the demographic explanatory variables because they would most affect 1999 poverty rates. Yet, persistent high poverty, for example, may depress education levels (or affect other demographic

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[9] The calculated t-statistic equaled 2.37, and was calculated as the difference between the two coefficients divided by the square root of the sum of the estimated coefficient variances.

[10] Abstracting from population change and existing worker effects for the moment, the percentage-point change in poverty (Δpov) depends on the probability each new job lifts a person out of poverty (pr($exit$)), and the increase in the employment rate, which is given by the employment growth rate (g) multiplied by the initial employment rate (er): Δpov = pr($exit$)(g)(er). For equal values of pr($exit$) 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 pr($exit$) 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 (pr($exit$)) because of growth.

[11] Because industry composition likely differs between PP and remaining counties, we also reestimated the base model by adding the seven industry employment shares described in note "c" of table 1 (not shown). The results continue to suggest that job growth has considerably greater poverty-reducing effects in PP counties than in non-PP counties [respective employment growth coefficients: -0.050 (t = 3.10) and -0.020 (t = 4.19)].

[12] Another potential difference worth noting is that there is a statistically significant greater poverty-reducing impact from a greater population share with an associate's degree in PP counties than non-PP counties (t = 1.69).

[13] We considered whether the models were somewhat over-fit and susceptible to multicollinearity by omitting the state fixed effects from the models. Though the resulting regression coefficients tended to be slightly larger than those reported in columns [3] and [5], the parameters were quite stable. For example, the 1995–2000 employment growth coefficient increased to -0.074 (t = 4.22) in the PP sample and increased to -0.030 (t = 6.05) in the non-PP sample.

[14] The first-stage instruments include the 1990–1995 job growth rate, the predicted 1995–2000 industry mix job growth rate from shift-share analysis, and the explanatory variables lagged 10 years as identifying instruments. Lagging the employment growth and other variables should mitigate any endogeneity of the other explanatory variables. Industry-mix employment growth is a common 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 (Bartik, 1991; Blanchard and Katz, 1992). The 1990–1995 job growth and the industry mix variables were highly significant in the first-stage model (F = 63.1), suggesting they were strong instruments (which also applied to the non-PP first-stage model, F = 85.0). Likewise, all 20 exogenous instruments were jointly significant at the 0.0000 level (in the PP first stage, F = 10.86, and in the non-PP first stage, F = 16.85). Staiger and Stock (1997) discuss the importance of strong first-stage instruments in two-stage least squares modeling.

traits), possibly creating endogeneity bias. However, dropping these control variables and estimating a small reduced-form model would likely produce severe omitted variable bias.

As a compromise to these competing problems, we specify a "conservative" model which lags the demographic variables 10 years (1990 and before) under the assumption that the lagged variables would be predetermined. All lagged variables are denoted in table 1 by showing the lagged year in bracketed italics. The economic variables—1995–2000 job growth and the two 1989 poverty measures—are not lagged. The resulting "conservative" models reported in columns [4] and [6] *also* treat employment growth as endogenous. Nonetheless, in these specifications employment growth has even stronger poverty-reducing impacts than in the base model, with the continuing pattern of a larger response in the PP sample. We can now be much more confident that endogeneity does not underlie the general patterns uncovered in columns [3] and [5].[15]

In other sensitivity analysis, to assess whether spatial clustering of the residuals was affecting the t-statistics, we reestimated the base model by assuming county residuals are correlated within their economic region, but independent of county residuals in other regions. The U.S. Bureau of Economic Analysis's 179 economic regions are used in this specification because they are constructed to form functional economic areas.[16] Yet these results (not shown) suggest the t-statistics are virtually identical to those in table 2, with the five-year job growth t-statistics being a little larger in this case.

Analysis of the Employment Growth-Poverty Linkage

Our conclusion is that place-based economic programs which successfully stimulate employment in PP counties reduce poverty by at least as much as in other counties. A probable reason for this finding is that job growth in PP counties is much less likely to attract migrants or commuters. This may occur because of uncertainties about their 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. Supporting this notion, the correlation between the 1990–2000 percentage change in employment and population was only 0.316 in PP counties, but 0.663 in non-PP counties—i.e., job growth is associated with fewer new residents to PP counties.

Despite potentially being tempered by in-migration, job growth likely reduces poverty rates by increasing the population share that is employed and reducing the unemployment rate. To better understand the channels through which job growth reduces poverty, we estimated four auxiliary regressions using the 2000 county unemployment rates and 2000 employment-population rates as the dependent variables. The model included the same right-hand-side variables as the "conservative" model in columns [4] and [6] which treats job growth as endogenous and lags the demographic variables by 10 years to help ensure they are predetermined. The key PP and non-PP county unemployment rate results are as follows:

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[15] Following Wooldridge (2002), the second-stage over-identification restrictions on the industry mix employment growth and 1990–1995 instruments could not be rejected at the 5% level in the PP model ($\chi^2_{[1]} = 2.97$), but could be rejected in the non-PP model ($\chi^2_{[1]} = 14.29$). Further analysis suggested the 1990–1995 employment growth rate may have been improperly excluded from the non-PP model. However, when it was added to the non-PP model in column [6] (not shown), our conclusions were not affected, whereas the 1990–1995 job growth rate coefficient was barely one-tenth the size of the corresponding 1995–2000 coefficient, indicating it was not of economic importance.

[16] The robust spatial residuals were estimated using the Stata Cluster command.

$$UR^{PP} = \underset{(4.48)}{-0.12}\, EMPGRTH_{1995\text{-}00} + \mathbf{X\beta}, \quad R^2 = 0.652,$$

$$UR^{Non\text{-}PP} = \underset{(3.65)}{0.04}\, EMPGRTH_{1995\text{-}00} + \mathbf{X\beta}, \quad R^2 = 0.533.$$

The corresponding employment-population results are:

$$EMPPOP^{PP} = \underset{(4.26)}{0.27}\, EMPGRTH_{1995\text{-}00} + \mathbf{X\beta}, \quad R^2 = 0.561,$$

$$EMPPOP^{Non\text{-}PP} = \underset{(0.93)}{0.04}\, EMPGRTH_{1995\text{-}00} + \mathbf{X\beta}, \quad R^2 = 0.746.$$

For PP counties, five-year employment growth is associated with a lower unemployment rate and a higher employment-population rate. In the employment rate equation, the 0.27 coefficient suggests that about one-fourth of new jobs over a five-year span go to original residents in PP counties, with the remainder going to new residents and commuters. Thus, the relative remoteness of PP counties may limit these offsetting responses. Conversely, in non-PP counties, five-year job growth is not associated with lower unemployment rates, nor does it statistically increase the employment rate, suggesting new residents and commuters take the newly created jobs. Hence, the apparent closer (regional) integration of non-PP county labor markets means local job growth has fewer poverty-reducing impacts.

The non-PP county findings are consistent with Blanchard and Katz's (1992) conclusion that positive employment shocks only temporarily reduce the unemployment rate and raise the employment-population rate at the state level, with the unemployment and employment rates both returning to their starting point after five years. It is also unlikely the effects on the employment rate in PP counties are mostly attributable to population composition effects—i.e, due to migrants having lower unemployment rates and higher employment rates than long-term residents. Bartik (1991) finds the effects of employment growth on labor force participation rates do not differ significantly across samples of all regional residents versus only long-term residents, while Bartik (1993) provides additional indirect evidence that in general the composition effect is likely to be modest at most.

To examine whether PP and non-PP counties respond differently to changes in the unemployment rate and the employment-population rate, we reestimated the base poverty model after adding male and female measures of the unemployment rate, employment-population rate, and the full-time employment share.[17] Inclusion of these variables allows us to ascertain some of the channels through which employment growth reduces poverty. These findings indicate PP county poverty rates are more responsive to changes in employment-population rates, whereas non-PP county poverty rates respond more to changes in unemployment rates (not shown). Thus, in PP counties, improving work prospects for all nonemployed residents—regardless of their official unemployment status—is most likely to reduce poverty rates. Nevertheless, even after accounting for the other labor-market measures, job growth still had a statistically

[17] To fully account for the county's economic structure and labor-force mobility, this fully specified model also included seven industry shares (see footnote "c" in table 1) and measures of residential mobility (see footnote "d" in table 1).

significant impact in reducing poverty—especially in PP counties. For example, strong growth may allow workers to upgrade from lower to higher paying positions (Felsenstein and Persky, 1999).

Alternative Specifications

Using the base specifications in columns [3] and [5], which estimate the total anti-poverty 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 percentage of the population living in households below 50% of the poverty threshold, whereas panel B does the same using the percentage of the population between 50%–100% 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, because the poverty population has been split, 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. 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 they face the strongest labor-force impediments.

Another question is: How far up the income distribution does job growth benefit low-income households? To examine this issue, panel C reports the corresponding results using the percentage of the population living between 100%–150% of the poverty distribution. In this case, job growth has a more ambiguous a priori impact because it lifts some of those below the poverty line to just above it, while it lifts some of those in the 100%–150% category further up the income distribution. Thus, it is not surprising the results suggest that job growth has almost no estimated impact for PP counties, implying the two effects offset. For non-PP counties, however, job growth reduces the share living between 100%–150% of poverty, indicating broader impacts up the income distribution, while the impacts below the poverty line are more limited.

Panels D, E, and F report sensitivity results 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 which have been historically more reliant on primary goods or manufacturing production. Specifically, the results in panel D test the possibility that job growth has a different impact in counties tied to more traditional base sectors (either more or less, especially if less-skilled workers are more tied to base sectors). Using an above-average 1990 male and female employment rate as the measure of historic tightness, panel E tests whether job growth has different effects in PP counties which have historically had tighter labor markets. 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, it is possible that in PP counties with a relatively higher educational attainment, greater job growth may have larger poverty-reducing impacts because potential employers may find it advantageous to hire original residents.

Table 2. Sensitivity Analysis of Persistent/Non-Persistent Poverty Regressions

Model Description	[1] 1999 PP Counties	[2] 1999 Non-PP Counties
A. Dependent Variable = % of Population < 50% Poverty Line		
▸ Lagged % Population < 50% of Poverty Line	0.33 (8.97)	0.34 (15.45)
▸ 1989 Surrounding County Average Poverty Rate	0.06 (2.19)	0.04 (5.05)
▸ % 1995–2000 Employment Growth	-0.023 (2.19)	-0.007 (2.74)
▸ R^2	0.78	0.76
B. Dependent Variable = % Population 50%–100% of Poverty Line		
▸ Lagged % Population between 50%–100% of Poverty Line	0.29 (7.17)	0.33 (16.70)
▸ 1989 Surrounding City Average Poverty Rate	0.09 (3.60)	0.09 (8.93)
▸ % 1995–2000 Employment Growth	-0.035 2.86)	-0.015 (4.80)
▸ R^2	0.74	0.81
C. Dependent Variable = % Population 100%–150% of Poverty Line		
▸ Lagged % Population between 100%–150% of Poverty Line	0.21 (3.48)	0.34 (18.92)
▸ 1989 Surrounding County Average Poverty Rate	0.03 (1.08)	0.08 (7.74)
▸ % 1995–2000 Employment Growth	0.004 (0.33)	-0.012 (3.66)
▸ R^2	0.49	0.80
BASE MODEL DEPENDENT VARIABLE = % of Population < Poverty Line:		
D. High 1990 Primary and Manufacturing Shares × 1995–2000 Employment Growth [a]		
▸ *F*-statistic for High Primary- and High Manufacturing-Employment × Employment Growth interactions	0.36 ($p = 0.700$)	0.60 ($p = 0.548$)
E. High 1990 Female and Male Employment/Population Rates × 1995–2000 Employment Growth [b]		
▸ *F*-statistic for the High Employment/Population × Employment Growth interactions	0.66 ($p = 0.520$)	0.08 ($p = 0.928$)
F. Education Attainment × 1995–2000 Employment Growth		
▸ % High School × 1995–2000 Employment Growth	NA	0.002 (1.59)
▸ % Some College × 1995–2000 Employment Growth	NA	-0.002 (1.52)
▸ % Associate Degree × 1995–2000 Employment Growth	NA	-0.004 (1.74)
▸ % College Graduate × 1995–2000 Employment Growth	NA	0.002 (2.93)
▸ % 1995–2000 Employment Growth	NA	-0.063 (0.89)
▸ *F*-statistic for the Education × Employment Growth interactions	0.13 ($p = 0.973$)	6.43 ($p = 0.000$)

(continued . . .)

Table 2. Continued

Table Footnotes:

Notes: The models use the column [3] and column [5] explanatory variables of table 1, except that models A, B, and C substitute the appropriate lagged 1989 dependent variable. The full set of results is available from the authors upon request. Unless indicated as a *p*-value, the values in parentheses are the robust *t*-statistics. 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% level.

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

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

In all three cases, the additional employment interactions are nowhere close to being jointly statistically significant in the PP specifications. 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. So, development policies that stimulate employment growth can successfully reduce poverty across a wide range of PP counties regardless of their initial structural characteristics—i.e., PP counties may not be hopeless "poverty traps." Indeed, in the first-stage 1995–2000 employment growth models described above, the 1989 county poverty rate and surrounding county poverty rate were insignificant in both the PP and non-PP specifications. Likewise, in the PP sample, lagged 1990 education, population, degree of rurality, female head population share, and racial composition were generally far from being statistically significant, further indicating they are not predisposed by their characteristics to suffer low employment growth. In fact, among nonmetropolitan PP counties, over one-third achieved a 1995–2000 job growth rate exceeding the 7% median value for nonmetropolitan non-PP counties.

The Geographical Heterogeneity of PP County Responses

The spatial location of a county may alter its data-generating process through either spatial dependence, where the outcomes in neighboring counties spill over and affect the county in question, or spatial heterogeneity, where the regression parameters differ by location. Given the large geographic size of the counties, the most reasonable spatial dependence arises through spatial error dependence (spatial autocorrelation), in which shocks in one county's spillover affect the residuals in neighboring counties. Sensitivity analysis suggested that spatial autocorrelation in the residuals might exist in the base model. Yet, consistent with our findings discussed above when correcting *t*-statistics for clustering in the residuals, further investigation confirmed our regression results were essentially unchanged when correcting for spatial autocorrelation using other methods.[18] Consequently, we did not pursue further spatial autocorrelation corrections.

[18] Spatial autocorrelation may exist because (*a*) a labor-demand shock in a county spills over and affects neighboring county labor markets, and (*b*) administrative boundaries do not reflect the socioeconomic boundaries (or markets) of the process in question, creating measurement error (LeSage, 1999, chap. 1). This differs from spatial heterogeneity in the underlying parameters (which GWR techniques address). An empirical complication arises because standard spatial autocorrelation tests often do not have the power to distinguish between spatial heterogeneity and spatial error dependence. For instance, the

As described in the previous section, there are reasons to expect the true regression coefficients to vary across the counties, and in particular, across the various poverty-cluster groups (i.e., spatial heterogeneity). 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 in the county-specific intercept). The GWR regression results are summarized in table 3, and unlike the spatial error model results, the GWR results are different than our previously reported results.

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% level, suggesting the GWR approach is appropriate. The AIC test procedure was minimized when the local sample size equaled 371, with the nearest neighbors receiving by far the most weight.[19] By contrast, if all 3,028 counties had 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). For PP counties, which tend to be dispersed throughout the country, such pooling means that the typical local PP-county sample would have included several hundred non-PP counties and few PP counties. Much of the PP/non-PP heterogeneity would have been washed out, akin to what usually occurs when pooling a quite small distinct sample with a much larger sample.[20] Indeed, the reason for dividing the PP and non-PP samples would be lost in this analysis (see footnote 7).

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 counties. The remaining columns report statistics for the individual coefficients ranging from their minimum to maximum values. The median value across all 381 counties is generally similar to the global regression results reported in column [3] of table 1, though there are a few cases where there are differences such as education.

Column [1] of table 3 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 little variation in responsiveness. The GWR median PP-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. When we estimated the non-PP

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determinants of poverty rates in rural Mississippi and rural Iowa counties likely differ somewhat. Similarly, there is usually a positive spatial correlation 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, when pooling the model, this type of spatial heterogeneity will produce a positive correlation between the residuals [e.g., the model consistently over- (under-) forecasts poverty in rural Iowa (Mississippi)]. Yet, this slight misspecification is 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 (or administrative boundaries creating measurement error), which would require a spatial clustering or spatial error dependence correction (also see McMillen, 2003b, 2004).

[19] 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, Brunsdon, and Charlton, 2002). 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.

[20] Illustrating how the pooled 3,028-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.

Table 3. Overview of the Persistent-Poverty County GWR Regression Coefficients

Variable[a]	p-Value[b]	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
County Intercept	0.000***	-8.717	0.608	9.140	12.873	14.896
Lagged 1989 Poverty Rate	0.13†	0.391	0.422	0.448	0.462	0.475
1989 Surrounding County Avg. Poverty	0.02*	0.041	0.048	0.063	0.085	0.189
% 1995–2000 Employment Growth	0.95	-0.087	-0.079	-0.077	-0.075	-0.071
1995–2000 Structural Change	0.05*	7.150	8.360	9.938	15.039	28.665
Population × Structural Change	0.23	-0.0005	-0.0002	-0.0002	-0.0001	-0.0001
Metro Area Population	0.01**	-1.0E-06	-1.0E-06	0.000	0.000	2.0E-06
County Population	0.50	7.0e-06	8.0e-06	9.0e-06	1.1e-05	2.2e-05
County Pop. × Nonmetro County Indicator	0.45	-1.6e-05	-8.0e-06	-7.0e-06	-6.0e-06	-3.0e-06
% Pop. that Immigrated between 1995–2000	0.28	-0.042	0.314	0.438	0.446	0.526
% Pop. that Immigrated between 1990–1994	0.24	0.185	0.252	0.307	0.501	0.896
% HS Graduate (age ≥ 25 yrs.)	0.65	-0.163	-0.145	-0.130	-0.117	-0.094
% Some College, No Degree (age ≥ 25 yrs.)	0.33	-0.210	-0.203	-0.193	-0.183	-0.065
% Associate Degree (age ≥ 25 yrs.)	0.69	-0.346	-0.254	-0.227	-0.200	-0.180
% Bachelor's Degree or more (age ≥ 25 yrs.)	0.25	-0.067	-0.013	0.009	0.021	0.059
% Households Female-Headed w/Children	0.04*	0.286	0.563	0.610	0.631	0.774
% Households Male-Headed w/Children	0.96	0.304	0.429	0.443	0.460	0.498
% Pop. African-American	0.15†	-0.085	-0.063	-0.057	-0.056	-0.053
% Pop. Other Race (non-Caucasian, Black)	0.55	-0.016	-0.004	0.005	0.010	0.019
% Pop. Hispanic	0.01**	-0.065	-0.037	-0.029	-0.022	-0.017
% Pop. Children < 7 Years Old	0.000***	-0.502	-0.462	-0.378	-0.082	0.339
% Pop. Children 7–17 Years Old	0.72	0.267	0.292	0.316	0.362	0.405
% Pop. Adults 18–24 Years Old	0.000***	0.029	0.081	0.137	0.307	0.486
% Pop. Adults 60–64 Years Old	0.06††	-0.223	0.025	0.149	0.286	0.595
% Pop. over 65 Years Old	0.000***	-0.048	-0.040	-0.008	0.155	0.326
N[c]	381					
R^2 GWR model	0.847					
R^2 OLS model	0.816					
F-statistic of geographic variation in the model[d] / (p-value)	3.7918 (5.3E-07***)					

Note: Significance levels are denoted as follows: ***0.1% level, **1% level, *5% level, ††10% level, and †15% level.
[a] See the notes to table 1 for definitions of variables.
[b] The significance of the null hypothesis that the regression coefficient does not vary across all PP counties.
[c] The bandwidth or the local number of PP counties used in the estimation of each county's individual regression coefficients equaled 371 (i.e., number of "neighbors"). See Fotheringham, Brunsdon, and Charlton (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.

sample using GWR, the *most* negative response for the 2,647 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 there could be large anti-poverty benefits from place-based economic development in PP counties, and all would fairly equally benefit from growth.

In contrast to job growth, there are 12 variables whose coefficients vary across PP counties based on a (liberal) 15% significance level. While all are 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.

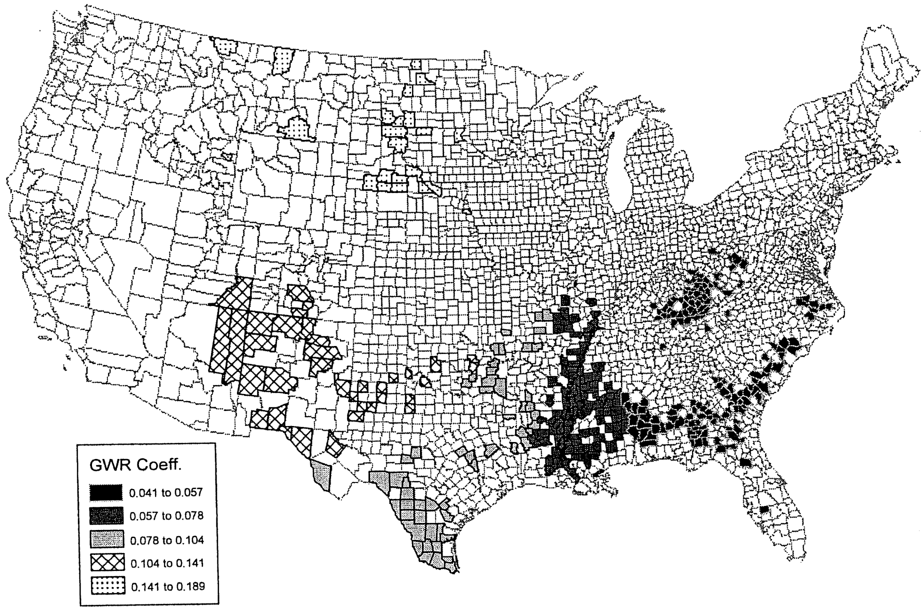

Figure 2. GWR variation in the average surrounding county regression coefficient

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 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 regions. The strongest spillover effects from neighboring counties occur in the Western and Great Plains PP counties having 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 reports 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. Hence, these counties would especially benefit from policies providing 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.[21]

[21] When mapping the GWR coefficients for the percentage of the population that is less than 18 years old (not shown), the clustering of the largest (most positive) coefficients fairly closely corresponds to the geographic clustering of the female-head coefficients. This further affirms the arguments for place-based supports for daycare. In fact, there was also a similar geographic clustering pattern for the 65-and-over population share coefficients (not shown).

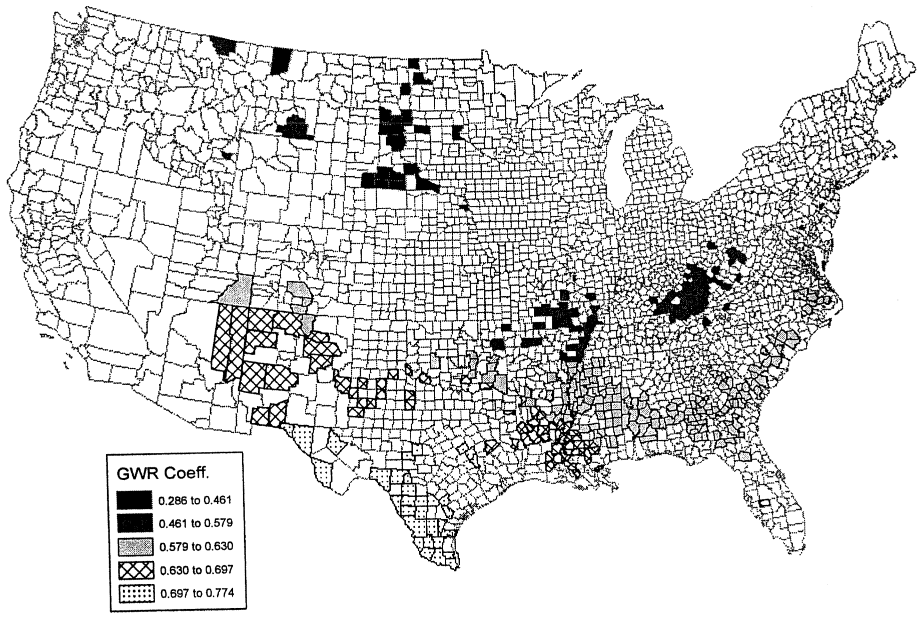

Figure 3. GWR variation in the female-headed family with children regression coefficient

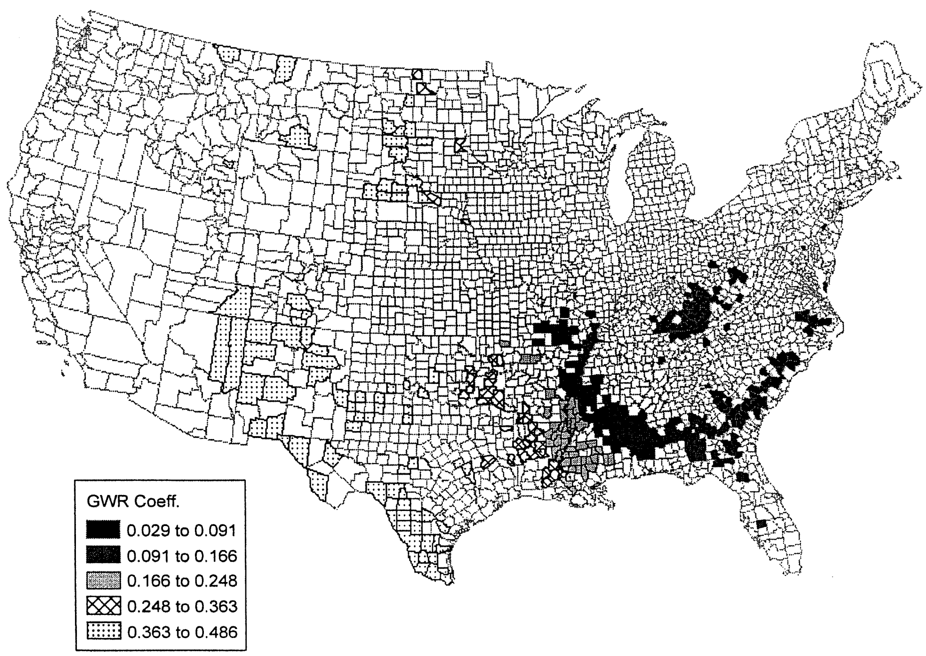

Figure 4. GWR variation in the share of 18–24 years of age regression coefficient

Another key variable is the population share between ages 18 and 24 because this cohort often lacks labor-market experience. As shown in table 3, this coefficient varies from 0.029 to 0.486 across PP counties. 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.

Conclusion

Economists have long debated the relative merits of antipoverty programs designed to help people versus those that help their places. This debate particularly applies to 381 persistent poverty (PP) counties in the United States because the relative severity and persistence of their economic deprivation have commonalities with poverty traps found in developing nations. Descriptive statistics reveal PP counties not only have populations with characteristics that place them at a higher poverty risk, they also generally have 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 include a place-based economic development component. If cultural, geographic, or institutional factors limit the hiring of local disadvantaged workers, increased economic activity would have only marginal impacts in reducing poverty—suggesting these counties resemble "poverty traps."

Standard regression analysis over a variety of specifications revealed that weaker (stronger) job growth causes much larger increases (decreases) in poverty in PP counties than in non-PP counties. This finding applied even when accounting for industry composition and demographic characteristics. Further assessment indicated job 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 likely has the most severe person-based impediments. The GWR results further confirmed a much stronger impact by employment growth in PP counties. For example, the poverty-reducing impact 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 among the 2,647 non-PP counties. The GWR results also suggested 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.

Moreover, the standard regression results showed 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 responsiveness to neighboring county poverty. This finding provides further evidence that PP counties may be pulled out of poverty under improved economic conditions.

While the GWR analysis did not reveal spatial variation in the poverty effects of job growth across PP counties, up to one-half of the variable regression coefficients had statistically significant geographical variation. For example, the GWR approach identified the most adverse impacts of the female-headed families with children share along the Rio Grande and in the lower Mississippi Delta region, whereas the 18- to 24-year-old age share had its most adverse impacts in Western PP counties. Thus, policies providing 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 geographic basis.

In summary, our findings suggest that American PP counties are not hopeless poverty traps, and their deprivation can be reduced with better economic opportunities. Accordingly, place-based 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 climate currently underlying American welfare policies. 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. Thus, the next logical research step is to determine both the likelihood that economic development policies can create jobs in each of the PP clusters, and what the best economic development approaches would be. It may be that the geographic component of some counties induces a high poverty outcome through persistently weak employment conditions, rather than through an inability to benefit from job growth. Yet, we did not find any evidence to indicate employment growth could not be stimulated in PP counties. The answers to these questions likely vary across clusters, requiring a strong geographical dimension to this research.

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References

Allard, S. W., R. Tolman, and D. Rosen. "Proximity to Service Providers and Service Utilization Among Welfare Recipients: The Interaction of Place and Race." *J. Policy Analy. and Mgmt.* 22,4(2003): 599–613.

Barkley, D. L., M. S. Henry, and S. Bao. "Identifying 'Spread' versus 'Backwash' Effects in Regional Economic Areas: A Density Functions Approach." *Land Econ.* 72,3(1997):336–357.

Bartik, T. J. "Who Benefits from State and Local Economic Development Policies?" W. E. Upjohn Institute for Employment Research, Kalamazoo, MI, 1991.

———. "Who Benefits from Local Job Growth: Migrants or the Original Residents?" *Regional Studies* 27,4(1993):297–311.

———. "Jobs for the Poor: Can Labor Demand Policies Help?" Russell Sage Foundation, New York, 2001.

Blanchard, O., and L. F. Katz. "Regional Evolutions." Brookings Papers on Economic Activity, No. 1-75, Washington, DC, 1992.

Blank, R. M. "Poverty, Policy, and Place: How Poverty and Policies to Alleviate Poverty Are Shaped by Local Characteristics." *Internat. Regional Sci. Rev.* 28,4(2005):441–464.

Borjas, G. J. "The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market." *Quart. J. Econ.* 118,4(2003):1335–1374.

Crandall, M. S., and B. A. Weber. "Local Social and Economic Conditions, Spatial Concentrations of Poverty, and Poverty Dynamics." *Amer. J. Agr. Econ.* 86,5(2004):1276–1281.

Davis, E. E., L. S. Connolly, and B. A. Weber. "Local Labor Market Conditions and the Jobless Poor: How Much Does Local Job Growth Help in Rural Areas?" *J. Agr. and Resour. Econ.* 28,3(2003): 503–518.

Easterly, W. *The Elusive Quest for Growth.* Cambridge, MA: MIT Press, 2001.

Felsenstein, D., and J. Persky. "When Is a Cost Really a Benefit? Local Welfare Effects and Employment Creation in the Evaluation of Economic Development Programs." *Econ. Develop. Quart.* 13,1(1999):46–54.

Fotheringham, A. S., C. Brunsdon, and M. Charlton. *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships.* Chichester, UK: Wiley, 2002.

Gibbs, R. M. "The Information Effects of Origin on Migrants' Job Search Behavior." *J. Regional Sci.* 34,2(1994):163–178.

Glaeser, E. L. "Are Cities Dying?" *J. Econ. Perspectives* 12,2(1998):139–160.

Glasmeier, A. K., and T. L. Farrigan. "Poverty, Sustainability, and the Culture of Despair: Can Sustainable Development Strategies Support Poverty Alleviation in America's Most Environmentally Challenged Communities?" *Annals of Amer. Academy of Political and Social Sci.* 590,0(2003): 131–149.

Greenwood, M. J. "Internal Migration in Developed Countries." In *Handbook of Population and Family Economics*, Vol. 1B, eds., M. R. Rosenzweig and O. Stark, pp. 647–720. Amsterdam: North-Holland, 1997.

Gundersen, C., and J. P. Ziliak. "Poverty and Macroeconomic Performance Across Space, Race, and Family Structure." *Demography* 41,1(2004):61–86.

Gyourko, J., and J. Tracy. "The Importance of Local Fiscal Conditions When Analyzing Local Labor Markets." *J. Polit. Econ.* 97,5(1989):1208–1231.

Henry, M. S., D. L. Barkley, and S. Bao. "The Hinterland's Stake in Metropolitan Area Growth." *J. Regional Sci.* 37,3(1997):479–501.

Jalan, J., and M. Ravallion. "Geographic Poverty Traps? A Micro Model of Consumption Growth in Rural China." *J. Appl. Econometrics* 17,4(2002):329–346.

Leichenko, R. M. "Does Place Still Matter? Accounting for Income Variation Across American Indian Tribal Areas." *Economic Geography* 79,4(2003):365–386.

LeSage, J. P. *The Theory and Practice of Spatial Econometrics*, 1999. Online. Available at www.spatial-econometrics.com/html/sbook.pdf. [Accessed October 2, 2006.]

Levernier, W., M. D. Partridge, and D. S. Rickman. "The Causes of Regional Variations in U.S. Poverty: A Cross-County Analysis." *J. Regional Sci.* 40,3(2000):473–498.

Lucas, R. E. B. "The Effects of Proximity and Transportation on Developing Country Population Migrations." *J. Econ. Geography* 1,3(2001):323–339.

Madden, J .F. "Changes in the Distribution of Poverty Across and Within the U.S. Metropolitan Areas, 1979–89." *Urban Studies* 33,9(1996):1581–1600.

McMillen, D. P. "Neighborhood House Price Indexes in Chicago: A Fourier Repeat Sales Approach." *J. Econ. Geography* 3,1(2003a):57–73.

———. "Spatial Autocorrelation or Model Misspecification?" *Internat. Regional Sci. Rev.* 26,2(2003b): 208–217.

———. "Employment Densities, Spatial Autocorrelation, and Subcenter in Large Metropolitan Areas." *J. Regional Sci.* 44,2(2004):225–243.

Miller, K. K., and B. A. Weber. "Persistent Poverty and Place: How Do Persistent Poverty Dynamics and Demographics Vary Across the Rural-Urban Continuum?" *Measuring Rural Diversity* 1,1(2004):1–8 [Southern Rural Development Center]. Online. Available at http://www.rupri.org/rprc/miller_weber.pdf. [Accessed October 13, 2006.]

Nord, M. "Poor People on the Move: County-to-County Migration and the Spatial Concentration of Poverty." *J. Regional Sci.* 38,2(1998):329–361.

Partridge, M. D., and D. S. Rickman. "Do We Know Economic Development When We See It?" *Rev. Regional Stud.* 33,1(2003):17–39.

———. "Persistent High-Poverty in Nonmetropolitan America: Can Economic Development Help?" *Internat. Regional Sci. Rev.* 28,4(2005):415–440.

———. "An SVAR Model of Fluctuations in U.S. Migration Flows and State Labor Market Dynamics." *S. Econ. J.* 72,4(2006a):958–980.

———. "The Geography of American Poverty: Is There a Role for Place-Based Policy?" W. E. Upjohn Institute for Employment Research, Kalamazoo, MI, 2006b.

Peters, A. H., and P. S. Fisher. "State Enterprise Programs: Have They Worked?" W. E. Upjohn Institute for Employment Research, Kalamazoo, MI, 2002.

Ravallion, M., and Q. T. Wodon. "Poor Areas, or Only Poor People?" *J. Regional Sci.* 39,4(1999):689–711.

Spilimbergo, A., and L. Ubeda. "Family Attachment and the Decision to Move by Race." *J. Urban Econ.* 55,3(2004):478–497.

Staiger, D., and J. H. Stock. "Instrumental Variable Regressions with Weak Instruments." *Econometrica* 65,3(1997):557–586.

Stoll, M. A. "Spatial Job Search, Spatial Mismatch, and the Employment and Wages of Racial and Ethnic Groups in Los Angeles." *J. Urban Econ.* 46,1(1999):129–155.

U.S. Department of Agriculture, Economic Research Service, Briefing Room. "Rural Income, Poverty, and Welfare: High Poverty Counties." Online. Available at http://www.ers.usda.gov/Briefing/IncomePovertyWelfare/HighPoverty/analysis.htm. [Accessed December 14, 2004.]

Wooldridge, J. W. *Econometric Analysis of Cross-Section and Panel Data.* Cambridge, MA: MIT Press, 2002.

Yankow, J. J. "Migration, Job Change, and Wage Growth: A New Perspective on the Pecuniary Return to Geographic Mobility." *J. Regional Sci.* 43,3(2003):483–516.