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Typology of American Poverty

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This analysis seeks to better understand the geography of American poverty over time. Cluster analysis is used to group 34,908 minor civil divisions according to their similarity in mean-centered poverty rates from 1980 to 2000. Logistic regression is used to asses the groupings' statistical validity and accuracy. Results identify twelve statistically distinct groupings and that over three thousand subcounty places had poverty rates of nearly 20 percent above the national average going back to 1980. However, less than 50 percent of these fall within the U.S. Department of Agriculture's Persistent Poverty Counties. The new typology shows the diversity of poverty in terms and identifies places based on poverty's relative severity. The typology also uniquely identifies places that moved into and out of high poverty and identifies many poor places that are "statistically invisible" using existing typologies. Results show that correlates of poverty identified in the literature generally hold true across smaller geographic scales.

Keywords: *poverty; regional economics; spatial analysis*

Social scientists studying poverty in the United States are confronted with a paradox—that economic growth appears to operate independently of poverty rates. Gross domestic product in the United States has grown by about 3.5 percent annually in real terms since the 1970s (Seskin and Smith 2006). However, poverty rates have failed to drop in a similar fashion, changing only a point to two each decade and stubbornly ranging between 11 and 12 percent (DeNavas-Walt, Proctor, and Lee 2006). This paradox suggests that the benefits of economic growth have been concentrated in a few places and have not diffused uniformly across the nation. This has led some to conclude that although the developed world is now one of the most prosperous areas, it also has one of the highest concentrations of deprivation (Hamnett 2003, 57–59).

There is a need to better understand the dynamics of poverty across time and space to see how economic well-being is concentrated. Previous research has clearly demonstrated that poverty persists in the United States across regions over

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Author's Note: Research for this article was done while the author was an assistant professor of agricultural economics at the University of Nebraska–Lincoln. An earlier version of this article was presented at the 70th annual meeting of the Rural Sociological Society in Santa Clara, California.

time (Joliffe 2004; Lobao 2004; Lobao and Saenz 2002; McLaughlin 2002; Partridge and Rickman 2006; Weber et al. 2005). This body of work has demonstrated that poverty can be explained by differences in economic structures, individuals, natural resources, geography, and past history. However, there have been almost no empirical studies specifically looking at the spatial distribution of American poverty across geographic places and time periods (Lobao and Hooks 2007; Weber et al. 2005). Almost none of the empirical work to date has examined poverty at subcounty geographies that represent places (Irwin 2007). This leaves several questions unanswered in the poverty literature. Are there subcounty places of persistently high poverty over time? Do certain places move into or out of high poverty over time? What are the socioeconomic characteristics of these places? Does a more detailed typology enhance our understanding of place-based poverty?

Recent advances in geographic information systems now allow us to address these questions more fully. This analysis has two main objectives. The first is to create a statistically valid typology of poverty in the United States across subcounty places and time periods. Cluster analysis is used to group places according to their similarity in poverty rates from 1980 through 2000. Logistic regression is then used to asses the statistical validity and accuracy of the groupings. The second objective is to describe poverty groups in terms of their demographic and economic characteristics. A general linear model is used to test significant mean differences across the groupings. The analysis is unique in terms of space, using subcounty minor civil divisions (MCDs) to approximate places. It is unique in terms of time, using geographically corrected subcounty data from 1980 through 2000. It is unique in terms of methods, using cluster analysis and logistic regression to identify statistically rigorous groupings. The new poverty typology fills an existing gap in the poverty literature by identifying and describing the geography of poverty across places over time.

The most commonly used typology of poverty is the Persistent Poverty County Codes, produced by the U.S. Department of Agriculture's (USDA) Economic Research Service. USDA defines persistently poor counties as those with poverty rates of 20 percent or more each year in 1970, 1980, 1990, and 2000 (Cook and Mizer 1994; Joliffe 2004). This typology has many advantages that have made it the de facto national standard for identifying poor places. The typology is easy to understand and interpret because of its relatively straightforward methods. It incorporates historical data for a long-term perspective yet is relatively current. It is comprehensive in geographic coverage, covering all counties in the United States. Last, it is widely used and understood by policy makers and researchers.

This analysis expands on the basic purpose of the USDA typology to allow a more full understanding of place-based poverty. First, instead of using a single arbitrary criterion across years to identify poor places, this analysis bases its thresholds on the unique distribution of the data in each census period. Second, this analysis takes into account the severity of poverty by distinguishing between extremely poor places (e.g., poverty rates of 50 percent or more) and those just over the average poverty rate for the nation (e.g., poverty rates of 18 percent). Third, instead of looking at a single rate over time, this analysis explicitly incorporates components of change into the typology to identify places that moved into or out of high poverty. Last, the typology looks to make smaller poor places ‘‘statistically visible’’ by using subcounty geographies as the unit of analysis (Isserman 2005).

Research on Poverty and Places

A number of studies have demonstrated that place matters in understanding poverty, and a comprehensive review of this work is presented by Weber et al. (2005). The majority of these studies take a labor market approach to understanding poverty, which incorporates both individual and structural approaches within a spatial context (Cotter 2002; Lobao, Hooks, and Tickamyer 2007; McLaughlin 2002). These studies generally attempt to understand county-level poverty rates in terms of different demographic characteristics, family structure components, geographic locations, industrial compositions, and a host of other labor market factors (Albrecht, Albrecht, and Albrecht 2000; Crandall and Weber 2004; Levernier, Partridge, and Rickman 2000; Lobao 1990; Lobao, Rulli, and Brown 1999; Lobao and Schulman 1991; Partridge and Rickman 2005, 2006; Swaminathan and Findes 2004). A review of this work is presented below.

In terms of geography, almost all studies on poverty cited use counties as the unit of analysis. These studies argue that counties are most appropriate because their boundaries are relatively stable over time, there is a wide array of data available at that scale, and they are an appropriate ‘‘meso’’ unit between neighborhoods and states. However, recent work has emphasized the need for more subcounty analyses to see if the relationships between poverty and various socioeconomic factors hold across geographic scales (Lobao and Hooks 2007; Irwin 2007). The only known study to date using subcounty units is by Crandall and Weber (2004), who examined poverty rates across census tracts.

In addition, a majority of the poverty studies reviewed here include some type of control for metropolitan residence. The findings indicate that small metropolitan and suburban counties have lower poverty rates compared to nonmetropolitan counties. Several studies have also explicitly incorporated spatial statistics into their analyses (Crandall and Weber 2004; Partridge and Rickman 2005, 2006). This work finds that high poverty counties are spatially clustered and high adjacent poverty exerts a strong positive effect on local poverty rates.

In terms of demographic structure, the literature unanimously supports the finding that higher levels of educational attainment reduce county poverty rates, especially high school and associate’s degrees. A strong relationship is also found between greater numbers of single-headed families with children and high area poverty, especially among those headed by females. The impact minority populations have on poverty is less clear in the literature. Most studies show that larger populations of non–African American minorities tend to increase local poverty rates. However, the findings for African American populations are mixed. Nation-scale studies show that African American populations are associated with lower rates of poverty (Levernier, Partridge, and Rickman 2000; Partridge and Rickman 2005, 2006), while nonmetropolitan studies find increases in poverty rates (Albrecht, Albrecht, and Albrecht 2000; Lobao 1990; Lobao, Rulli, and Brown 1999). Most of the analyses also look at the effect of age structure and generally find that persons younger than age 24 tend to increase local poverty, while older persons older than age 64 tend to reduce poverty.

In terms of economic conditions, one of the strongest findings is that current poverty rates are highly dependent on previous poverty rates—indicating that poverty is path dependent. The majority of studies show that increases in labor force participation rates lead to lower poverty rates at the county level, especially for women. As one would expect, the literature also shows that higher unemployment rates lead to higher local poverty, and this effect is particularly strong for male unemployment. Several analyses include employment growth and industrial restructuring in their models explaining county poverty rates (Crandall and Weber 2004; Levernier, Partridge, and Rickman 2000; Partridge and Rickman 2005; Swaminathan and Findes 2004). The findings demonstrate employment growth strongly reduces local poverty, especially when counties are near metropolitan areas. Counties experiencing industrial structuring are more likely to have higher poverty rates, as are counties with a less diversified industrial base.

All of the studies reviewed here include industry employment variables to model local economic structure. One consistent finding across all studies is that employment in agriculture and natural resources tends to increase local poverty. Most also find that greater shares of employment in consumer services, trade, and government lead to higher local poverty. Higher employment in the services sector, broadly defined, has a moderate effect at increasing poverty rates. However, the direction of this effect changes when looking at specific services industries. Partridge and Rickman (2006) find that higher skill producer services have a strong impact at reducing poverty, while relatively lower skill consumer services tend to increase poverty rates (Partridge and Rickman 2005, 2006). For manufacturing and transportation, two traditional rural industries, the results are also mixed. National studies show that employment in manufacturing and transportation results in lower poverty rates overall, while employment in these two sectors tends to increase poverty rates in nonmetropolitan areas.

In short, the poverty literature identifies several geographic, demographic, and economic correlates affecting county poverty rates. In terms of geography, poor counties are spatially clustered where neighboring poverty affects local poverty;

and poverty tends to be higher in nonmetropolitan and core urban areas. Poverty is path dependent over time. In terms of demographics, single-headed families and minorities increase local poverty; and higher levels of education decrease poverty. In economic terms, poor places have lower labor force participation and higher unemployment rates. Employment in agriculture, natural resources, lower skill services, trade, and government is associated with higher rates of poverty. Nonpoor places tend to have more jobs in higher skilled producer services. Manufacturing and transportation tends to reduce poverty rates overall, but not in nonmetropolitan areas.

Data and Method

To better understand the geography of American poverty over time, this analysis applies statistical classification techniques to a unique set of spatial data. The units of analysis are census MCDs, which are used to approximate places. MCDs are subcounty units that represent cities, towns, townships, voting precincts, and census civil divisions. Although imperfect, MCDs best represent communities at the subcounty level because they provide mutually exclusive and exhaustive coverage, and they generally conform to local sociopolitical boundaries. By contrast, census-designated places are incomplete because they do not cover unincorporated areas, and census tracts are defined along minimum population thresholds that largely ignore sociopolitical concerns. However, the problem with MCDs, and most other subcounty units, is that the geographic boundaries change with each decennial census, making comparisons across time problematic. To correct for this problem, this analysis uses data from GeoLytics to recalculate data from previous census periods so that it is "normalized" to the 2000 census geographies.

Cluster analysis is then used to group all MCDs in the United States into homogenous groups according to their poverty rates from 1980 to 2000. Poverty rates indicate the percentage of noninstitutionalized adults whose before-tax incomes, excluding noncash benefits and not adjusting for regional differences in cost of living, are below the poverty line for their particular household type (U.S. Census Bureau 2002). To facilitate interpretation across years, poverty rates are centered using the grand mean (national average) for all MCDs in that census year. To remove spurious effects because of low population, $n = 256$ MCDs with fewer than ten people for whom poverty status was determined are dropped from the data, resulting in $N = 34{,}908$ MCDs for analysis. Descriptive statistics on poverty rates and centered rates are presented in Table 1.

Cluster analysis is the generic name for a wide array of procedures that can be used to create a classification (Blashfield and Aldenderfer 1978).[1] A clustering method is a multivariate statistical procedure that starts with data containing information about

Table 1
Descriptive Statistics of Poverty Rates for $N = 34{,}908$ Minor Civil Divisions from 1980 to 2000

Variable	n	Min	Max	M	SD	Variance
Poverty rate 1980	34,908	0.00	88.79	14.69	8.69	75.60
Poverty rate 1990	34,908	0.00	87.33	14.23	9.20	84.62
Poverty rate 2000	34,908	0.00	100.00	11.48	9.11	82.93
Centered poverty rate 1980	34,908	−14.69	74.10	0.00	8.69	75.60
Centered poverty rate 1990	34,908	−14.23	73.10	0.00	9.20	84.62
Centered poverty rate 2000	34,908	−11.48	88.52	0.00	9.11	82.93

Note: Centered variables are calculated using the grand mean.

a sample of entities and attempts to reorganize them into relatively homogenous groups (Everitt 1980). In this analysis, squared Euclidean distance is used to measure distances between clusters and MCDs based on centered poverty rates between 1980 and 2000. The formula for squared Euclidean distance is given in Equation 1, where d_{ij} is the distance between MCDs i and j, and x_{ik} is the value of the kth centered poverty variable for the ith MCD (Aldenderfer and Blashfield 1984).

$$d_{ij}^2 = \sum_{k=1}^{p} \left(x_{ik} - x_{jk}\right)^2 \tag{1}$$

Clusters and MCDs are joined together using Ward's minimum-variance method, which seeks to minimize the within-cluster sum of squares by merging two clusters from the previous generation until all MCDs are grouped into one cluster (Aldenderfer and Blashfield 1984). The formula for Ward's method is presented in Equation 2, where d_{pq} is a matrix of similarities between two clusters p and q, N is number of MCDs, d_{hk} is the most similar pair of points h and k, p is the cluster formed by merging points h and k, and q is all other clusters.

$$d_{pq} = \left(\frac{1}{N_p + N_q}\right)\left[\left(\left(N_q + N_h\right)d_{qh}\right) + \left(\left(N_q + N_k\right)d_{qk}\right) - N_q d_{hk}\right] \tag{2}$$

After the MCDs are grouped using cluster analysis, the solution is statistically validated using multinomial logistic regression, which can be used to predict membership on an endogenous categorical variable. The procedure assesses the importance of the covariates, estimates the odds of group membership, and assesses the accuracy of the classification. The logistic model is presented in Equation 3. The logit, denoted L, is the natural log applied to the odds ratio of an MCD being in certain cluster (Hosmer and Lemeshow 1989). The exogenous variables used in the analysis are the same used in the cluster analysis and include *CPOV80, CPOV90*,

Table 2
Results of Cluster Analysis Grouping $N = 34{,}908$ Minor Civil Divisions by Centered Poverty Rates from 1980 to 2000

Number of Clusters	Distance	R^2	Expected R^2	Semipartial R^2	Pseudo F	Pseudo t^2
20	0.3540	.8415	.9088	.0042	9,748.39	1,330.76
19	0.8240	.8373	.9056	.0042	9,975.82	207.48
18	0.5705	.8322	.9021	.0052	10,175.25	891.08
17	0.4532	.8264	.8983	.0057	10,384.17	712.97
16	0.3024	.8205	.8941	.0060	10,629.97	1,598.52
15	0.3263	.8139	.8895	.0066	10,900.59	1,941.44
14	0.7048	.8066	.8843	.0073	11,192.82	714.50
13	0.3502	.7987	.8784	.0079	11,538.76	2,278.76
12	0.9498	.7899	.8717	.0088	11,927.25	433.80
11	0.4481	.7798	.8641	.0101	12,360.05	1,819.04
10	0.6891	.7674	.8551	.0124	12,795.04	859.72
9	1.4134	.7523	.8446	.0151	13,251.73	436.91
8	0.3024	.7365	.8319	.0158	13,935.19	4,786.43
7	0.6255	.7170	.8162	.0195	14,735.74	2,432.68
6	0.7018	.6906	.7963	.0264	15,577.08	1,487.97
5	0.4161	.6623	.7700	.0283	17,111.64	3,377.44
4	0.3993	.6260	.7331	.0363	19,476.02	10,110.55
3	1.1505	.5673	.6751	.0587	22,880.95	2,015.04
2	0.6150	.4138	.5587	.1535	24,642.22	20,200.84
1	1.2930	.0000	.0000	.4138	—	24,642.22

Note: Values are calculated using squared Euclidean distance and Ward's hierarchical cluster method. Centered poverty rates were converted to ratios to minimize large elevation differences.

and *CPOV00*, representing centered poverty rates for 1980, 1990, and 2000, respectively.

$$L_i = 1n\left(\frac{P_i}{1-P_i}\right) = b_0 + b_1 CPOV80 + b_2 CPOV90 + b_3 CPOV00 + u_i \qquad (3)$$

Results

Identification of Clusters

The results of the cluster analysis indicate that the $N = 34{,}908$ MCDs can be clustered into 12 groups based on their centered poverty rates, accounting for nearly 80 percent ($R^2 = .79$) of the variance in the data. Based on the information presented in Table 2, the results indicate the presence of either nine or twelve clusters based on the loss of information diagnostics. The semipartial R^2 statistic indicates a large jump at stage 11, indicating 12 clusters. Jumps in pseudo t^2 at stages 13 and 11 indicate a 12- or 10-cluster solution. High values of pseudo F also indicate the presence of 9 or 12 clusters. The 12-cluster solution is chosen because it accounts for more variance and it produces more informative groupings than the 9 cluster solution. In addition, cluster analysis was run using other agglomerative methods (including average linkage, centroid method, and Gower's median method), but these cluster solutions accounted for only a small amount of the variance in the data ($R^2 < .40$), indicating a poor solution.

The 12-cluster solution is then statistically validated using multinomial logistic regression, with the clusters as the endogenous variables and centered poverty rates as the exogenous variables. The results are presented in Table 3 and indicate that the cluster solution can be reliably replicated and that it is highly accurate. Results of the –2 log likelihood test indicate that the model fits the data better than the intercept-only model, indicating the exogenous poverty variables contribute significantly to model fit ($\chi^2_{(33)} = 120{,}246.28$, $p > .001$). Pearson's χ^2 is highly significant ($\chi^2_{(383790)} = 361{,}316{,}662$, $p > .001$) and shows the model fits the data well. The Cox and Snell and Nagelkerke's pseudo-R^2 statistics show that the clusters can be reliably replicated from the poverty covariates.

A key feature of multinomial logistic regression is the ability to predict group membership from the covariate logistic model. Comparing predicted membership to observed membership gives an indication of how accurate the model performs in terms of classification. The results presented in Table 4 show that the model correctly predicted cluster membership for 85 percent of the MCDs. Although this overall accuracy rate is quite high, it varied greatly across clusters. For example, cluster *f* has the lowest rate of accuracy (64 percent) with misclassifications across clusters *e* and *g*.

In addition to assessing the performance of the cluster solution, logistic regression allows us to understand which variables drive the classification process (Cox and Snell 1989). This permits one to assign statistically valid names to the clusters rather than simply describing clusters based on their means. The names and descriptive statistics of the 12 clusters are presented in Table 5. To facilitate a better understanding of the results given space limitations, several of the clusters are grouped together for further analysis.

The Low Poverty Group is formed by merging the Low Stable Poverty Cluster (cluster a) and the Below Average Poverty Cluster (cluster b). The Declining High Poverty Group consists of the Very High Improving to Low Poverty Cluster (cluster d) and the Very High Improving to Average Poverty Cluster (cluster h). The Advancing High Poverty Group simply renames the Above Average Worsening to Very High Poverty Cluster (cluster i). Last, the High Poverty Group combines the High Stable Poverty Cluster (cluster j), the Very High Stable Poverty Cluster (cluster k), and the Very High Worsening to Extreme Poverty Cluster (cluster l).

Table 3
Results of Multinomial Logistic Regression Predicting Cluster Membership of $N = 34{,}908$ Minor Civil Divisions by Centered Poverty Rates from 1980 to 2000

Statistic	Cluster a	Cluster b	Cluster c	Cluster d	Cluster e	Cluster f	Cluster h	Cluster i	Cluster j	Cluster k	Cluster l
Intercept											
Logit coefficient *b*	–15.63	0.86	0.17	–10.05	3.37	–2.98	–28.96	–9.20	–12.39	–44.70	–32.51
SE	0.37	0.10	0.11	0.30	0.09	0.14	0.77	0.24	0.30	1.33	1.52
Wald statistic	1,758.51***	69.48***	2.62	1,128.59***	1,500.70***	480.25***	1,413.80***	1,453.58***	1,678.05***	1,124.63***	457.53***
Odds ratio exp(b)	—	—	—	—	—	—	—	—	—	—	–-
Centered poverty rate 1980											
Logit coefficient *b*	–2.14	–1.61	–0.94	0.77	–1.14	–0.63	1.21	–0.19	0.69	1.13	0.27
SE	0.03	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02	0.03	0.04
Wald statistic	4,935.49***	4,389.02***	1,700.15***	1,021.98***	2,580.94***	1,077.15***	1,623.79***	148.36***	1,272.56***	1,221.49***	48.96***
Odds ratio exp(b)	0.117	0.200	0.389	2.164	0.320	0.532	3.367	0.824	1.989	3.081	1.305
Centered poverty rate 1990											
Logit coefficient *b*	–2.17	–1.13	–0.83	–0.15	–0.58	0.57	1.25	0.31	0.54	1.45	0.59
SE	0.03	0.02	0.02	0.02	0.01	0.02	0.03	0.01	0.02	0.04	0.03
Wald statistic	4,875.71***	3,802.32***	2,254.45***	75.26***	1,506.30***	1,281.21***	1,549.93***	571.88***	1,247.36***	1,372.92***	388.94***
Odds ratio exp(b)	0.114	0.323	0.436	0.864	0.561	1.763	3.477	1.369	1.717	4.246	1.804
Centered poverty rate 2000											
Logit coefficient *b*	–1.63	–0.78	–1.58	–1.15	–0.11	–0.40	–0.49	0.72	0.21	0.59	1.18
SE	0.03	0.02	0.02	0.03	0.01	0.01	0.03	0.02	0.01	0.03	0.03
Wald statistic	3,665.09***	1,759.55***	5,447.64***	1,713.71***	107.65***	858.73***	361.99***	1,662.69***	263.10***	361.41***	1,134.92***
Odds ratio exp(b)	0.195	0.459	0.207	0.316	0.892	0.667	0.612	2.061	1.236	1.804	3.241
Goodness of Fit	AIC	BIC	–2 log likelihood	χ^2	Pseudo R^2						
Intercept model	149,418.11	149,511.20	149,396.11	—	Cox and Snell	.968					
Covariate model	29,237.83	29,610.09	29,149.83	120,246.28***	Nagelkerke	.982					
Pearson	—	—	—	3.6132E + 08***							

Note: Odds compared to membership in Cluster g. Akaike (AIC) and Bayesian (BIC) information criteria used to compare model iterations.
$*p < .05$. $**p < .01$. $***p < .001$.

Table 4
Accuracy of Multinomial Logistic Regression Comparing Predicted versus Observed Cluster Membership for $N = 34{,}908$ Minor Civil Divisions (MCDs) from 1980 to 2000

	Predicted												
Observed	Cluster a	Cluster b	Cluster c	Cluster d	Cluster e	Cluster f	Cluster g	Cluster h	Cluster i	Cluster j	Cluster k	Cluster l	Percentage Correct
Cluster a	5,398	352	68	0	0	0	0	0	0	0	0	0	92.78
Cluster b	216	6,576	300	0	264	0	0	0	0	0	0	0	89.40
Cluster c	218	213	4,258	18	333	48	46	0	0	0	0	0	82.94
Cluster d	0	0	86	827	0	0	64	23	0	38	0	0	79.67
Cluster e	5	352	130	0	4,136	140	343	0	5	0	0	0	80.92
Cluster f	0	1	46	36	152	705	141	12	4	3	0	0	64.09
Cluster g	0	0	148	81	208	42	3,630	0	114	77	0	0	84.42
Cluster h	0	0	0	33	0	10	0	451	1	73	17	0	77.09
Cluster i	0	0	0	0	58	26	73	0	1,143	134	4	11	78.88
Cluster j	0	0	0	10	0	32	130	49	88	1,713	37	3	83.07
Cluster k	0	0	0	0	0	0	0	28	14	28	716	11	89.84
Cluster l	0	0	0	0	0	0	0	0	10	3	21	124	78.48
Overall percentage	16.72	21.47	14.43	2.88	14.76	2.87	12.68	1.61	3.95	5.93	2.28	0.43	85.01

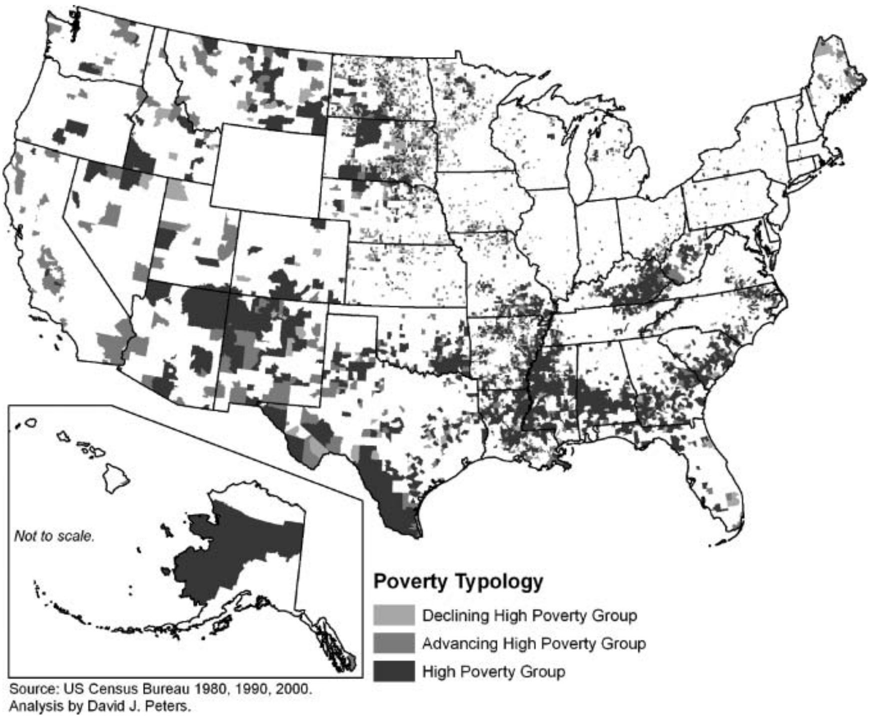
Note: Results of multinomial logistic regression predicting cluster membership of MCDs by poverty rates from 1980 to 2000.

Table 5
Poverty Typology Descriptive Statistics for $N = 34,908$ Minor Civil Divisions from 1980 to 2000

		Centered Poverty 1980		Centered Poverty 1990		Centered Poverty 2000	
Poverty Typology by Cluster	*N*	*M*	*SD*	*M*	*SD*	*M*	*SD*
a: Low stable poverty	5,818	−8.96	2.33	−9.80	1.92	−7.54	1.80
b: Below avg. stable poverty	7,356	−5.37	2.61	−4.74	2.58	−2.72	2.27
c: Avg. improving to low poverty	5,134	−0.53	3.85	−2.43	4.11	−6.68	3.15
d: Very high improving to low poverty	1,038	13.75	6.30	1.72	5.94	−6.44	4.52
e: Below avg. worsening to above avg. poverty	5,111	−1.84	3.17	−0.02	4.04	3.02	4.00
f: Avg. poverty, 1990 spike	1,100	0.30	4.09	11.18	4.27	−0.15	5.77
g: Above avg. stable poverty	4,300	5.42	3.08	3.74	3.92	3.87	4.09
h: Very high improving to avg. poverty	585	20.15	9.03	20.54	9.36	−0.47	7.91
i: Above avg. worsening to very high poverty	1,449	4.07	5.27	8.70	6.97	17.38	7.32
j: High stable poverty	2,062	13.60	4.89	11.59	5.89	9.92	5.74
k: Very high stable poverty	797	22.90	9.62	29.83	8.68	24.96	9.91
l: Very high worsening to extreme poverty	158	11.87	9.53	12.63	9.67	48.50	15.69

Note: Typology created by naming clusters based on multinomial logistic regression results.

Figure 1
Poverty Typology Groups for $N = 34{,}908$ Minor Civil Divisions from 1980 to 2000



Source: U.S. Census Bureau.

Description of Poverty Cluster Groups

The geographic distribution of the groups is presented in Figure 1. The High Poverty Group consists of 3,017 places that experienced poverty rates nearly 20 percent above the national average since 1980. These places contain 10.5 percent of the nation's poor and 4.7 percent of its population. The highest concentrations of poor places occur in Mississippi, Louisiana, Kentucky, New Mexico, and Arizona. The average population of these poor places is about 4,400, and most live in rural areas (only 13.3 percent urban). Population grew much more slowly compared to the Low Poverty Group, increasing only 2.6 percent since 1980.

Although the Advancing High Poverty Group contains fewer places (1,449 MCDs), it has more of the nation's poor (12.1 percent) and overall population

(6.2 percent) than the High Poverty Group. These places saw poverty rates jump from 4 percent above the national average in 1980 to nearly 14 percent above average by 2000. Places with worsening poverty tend to have larger and more urban populations, with an average size of 12,058 people, of whom 23.8 percent live in urban areas. However, these places experienced almost zero growth in population (0.1 percent) during the past 20 years. Most of the advancing high poverty places are located in West Virginia, California, New Mexico, Louisiana, and North Dakota. This indicates the development of new persistent high poverty places in previously average poverty areas.

By contrast, the 1,623 places in the Declining High Poverty Group experienced sizable reductions in poverty, dropping from nearly 20 percent above the national average in 1980 to less than 4 percent by 2000. These places are very small (484 people), and almost all of the population lives in rural areas (only 0.8 percent urban). Because of their small size, these poverty improvement areas contain only a small fraction of the nation's poor and overall population (both less than 0.5 percent). Furthermore, these places saw their populations drop by nearly 10 percent since 1980. This decline in population may partially explain drops in poverty rates, as the number of poor persons fell because of out-migration or natural decreases. States with the largest concentrations of declining poverty places include South Dakota, Arkansas, North Dakota, Minnesota, and Nebraska.

The demographic and economic characteristics of the poverty typology groups are presented in Tables 6 and 7. A general linear multivariate model is used to test significant mean differences across the groupings. Given that the typology categories have unequal group sizes and variances, the Dunnett's C statistic is used to test for significant differences, rather than the more commonly used Scheffe test. The discussion focuses on the significant differences between the High Poverty Group and other groups in the analysis. However, significance tests between the other groups are also reported for those interested in this information.

Demographic structure and change of the poverty typology groups are presented in Table 6. As one would expect, the High Poverty Group has the lowest median household income ($25,362) and the highest unemployment rate (4.3 percent) compared to the Low and Declining Poverty Groups. It is interesting to note that the Advancing High Poverty Group has income ($26,489) and unemployment rates (4.3 percent) only slightly higher than high poverty places, indicating that the two groups share similar economic conditions. Surprisingly, both high and advancing poverty places saw sizable declines in unemployment rates over the past 20 years (over 6.0 drop). However, income growth in the Advancing Group is far below (112.5 percent) that of the nonpoor groups and even the High Poverty Group (156.1 percent), which saw growth on par with low poverty places.

The High Poverty Group has significantly higher rates of minorities (27.6 percent), more work disabled people (14.4 percent), more single-headed families with children (9.5 percent), lower rates of high school and associate's degree holders

Table 6
Demographic Characteristics across Poverty Typology Groups for $N = 34{,}908$ Minor Civil Divisions from 1980 to 2000

	Poverty Typology Groups			
Percentage in 2000	High Poverty Group	Advancing High Poverty Group	Declining High Poverty Group	Low Poverty Group
Population (number)	$4{,}384^{DL}$	$12{,}058^{D}$	484^{HAL}	$11{,}132^{HD}$
Urban population	13.27^{ADL}	23.83^{HDL}	0.81^{HAL}	36.17^{HAD}
Minority population	27.64^{ADL}	17.84^{HDL}	7.09^{HAL}	5.72^{HAD}
Work disabled population	14.37^{ADL}	13.03^{HDL}	10.96^{HAL}	9.48^{HAD}
Single-headed families	9.52^{ADL}	8.82^{HDL}	3.74^{HAL}	6.20^{HAD}
High school or associate's degree	57.38^{ADL}	60.58^{HDL}	66.60^{HAL}	64.58^{HAD}
Bachelor's degree or higher	10.28^{ADL}	11.88^{HL}	12.53^{HL}	20.65^{HAD}
Median household income ($)	$25{,}362^{ADL}$	$26{,}489^{HDL}$	$34{,}845^{HAL}$	$47{,}898^{HAD}$
Unemployment	4.29^{DL}	4.25^{DL}	2.30^{HAL}	2.56^{HAD}
Percentage change from 1980 to 2000				
Population Δ	2.64^{DL}	0.14^{DL}	-9.87^{HAL}	26.30^{HAD}
Urban population Δ	11.44^{ADL}	16.12^{HD}	0.66^{HAL}	18.38^{HD}
Minority population Δ	2.98^{AD}	5.51^{HDL}	-1.13^{HAL}	2.66^{AD}
Work disabled population Δ	1.63	2.16^{D}	1.00^{AL}	1.92^{D}
Single-headed families Δ	1.48^{ADL}	2.88^{HDL}	0.10^{HAL}	1.17^{HAD}
High school or associate's degree Δ	18.49^{AL}	14.27^{HDL}	18.43^{AL}	9.31^{HAD}
Bachelor's degree or higher Δ	2.88^{DL}	2.78^{DL}	5.37^{HAL}	7.49^{HAD}
Median household income Δ (nominal)	156.05^{AD}	112.50^{HDL}	237.29^{HAL}	155.82^{AD}
Unemployment rate Δ	-6.50^{DL}	-6.24^{DL}	-5.11^{HAL}	-8.53^{HAD}

Note: Dunnett's C test statistic used to correct for unequal group sizes and variances. Significant differences at $p < .05$ between the High Poverty (H), Advancing High Poverty (A), Declining High Poverty (D), and Low Poverty (L) groups.

Table 7
Economic Characteristics across Poverty Typology Groups for $N = 34,908$ Minor Civil Divisions from 1980 to 2000

	Poverty Typology Groups			
Percentage in 2000	High Poverty Group	Advancing High Poverty Group	Declining High Poverty Group	Low Poverty Group
Agriculture, forestry, and mining	15.54^{ADL}	17.96^{HDL}	25.66^{HAL}	4.83^{HAD}
Construction	7.72^{AD}	6.90^{HL}	6.77^{HL}	7.56^{AD}
Transportation and utilities	5.46	5.42	5.34	5.44
Manufacturing	15.13^{ADL}	12.65^{HL}	12.80^{HL}	18.40^{HAD}
Trade	12.66^{DL}	12.88^{DL}	11.20^{HAL}	14.84^{HAD}
Information	1.22^{L}	1.40^{L}	1.24^{L}	2.20^{HAD}
Finance, insurance, and management	2.35^{DL}	2.42^{DL}	2.88^{HAL}	4.31^{HAD}
Professional services	1.54^{AL}	1.88^{HL}	1.76^{L}	4.14^{HAD}
Admin support, real estate, and rentals	2.72^{DL}	2.97^{DL}	2.03^{HAL}	3.65^{HAD}
Education services	9.06^{DL}	8.98^{DL}	7.85^{HA}	8.32^{HA}
Health care and social assistance	10.59^{L}	10.64	10.02^{L}	11.04^{HD}
Entertainment, food, and other services	10.55^{DL}	11.12^{D}	8.63^{HAL}	11.00^{HD}
Public administration	5.46^{ADL}	4.79^{HDL}	3.83^{HAL}	4.27^{HAD}
Percentage change from 1980 to 2000				
Agriculture forestry, and mining	-8.52^{DL}	-8.26^{DL}	-17.91^{HAL}	-4.93^{HAD}
Construction	0.56^{L}	0.62	1.13	1.07^{H}
Manufacturing	-3.92^{DL}	-3.81^{DL}	0.81^{HAL}	-7.42^{HAD}
Transport, communication, and utilities	1.29^{DL}	0.76^{D}	2.52^{HAL}	0.94^{HD}
Trade	-2.09^{AL}	-3.11^{HDL}	-1.43^{AL}	-3.81^{HAD}
Finance, insurance, and real estate	0.81^{DL}	0.59^{DL}	1.46^{HA}	1.17^{HA}
Services	11.27^{ADL}	12.51^{H}	12.60^{H}	12.72^{H}
Public administration	0.59^{L}	0.70^{L}	0.82^{L}	0.26^{HAD}

Note: Dunnett's C test statistic used to correct for unequal group sizes and variances. Significant differences at $p < .05$ between the High Poverty (H), Advancing High Poverty (A), Declining High Poverty (D), and Low Poverty (L) groups.

(57.4 percent), and fewer college graduates (10.3 percent) than the Declining and Low Poverty Groups. These significant differences are also replicated for the Advancing High Poverty Group when compared to the Declining and Low Poverty Groups. Although the Advancing Poverty Group has significantly different values than the High Poverty Group, the mean differences are small when compared to the other nonpoor groups. This indicates that advancing and high poverty places share many of the same demographic conditions, albeit at slightly different levels. These findings are consistent with the existing poverty literature, indicating that known demographic correlates of poverty hold across subcounty geographic scales.

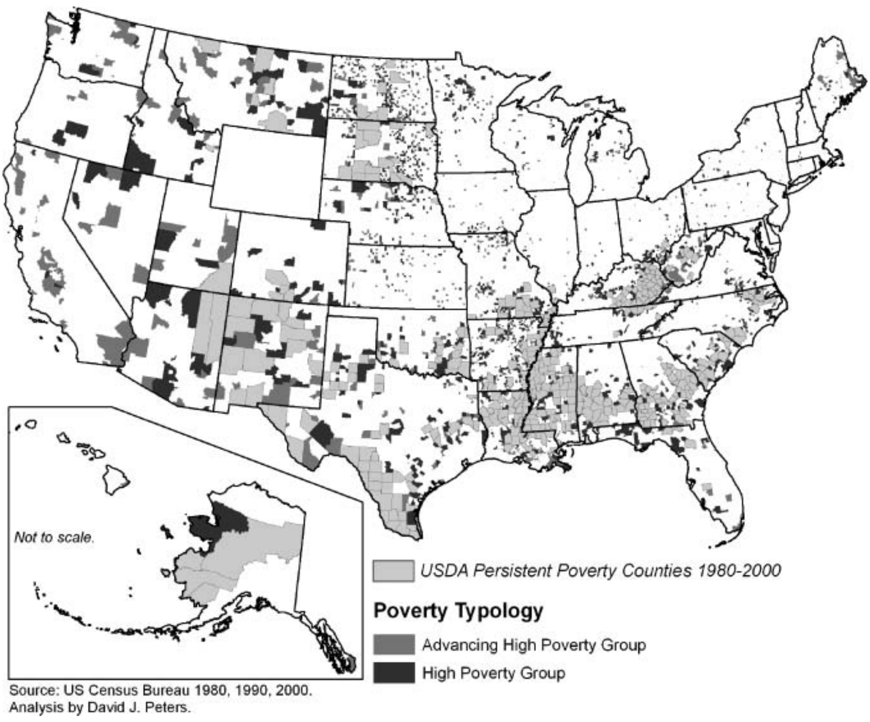
Looking at change from 1980, places with worsening high poverty saw the fastest growth in minority populations (5.5 percent) and single-headed families with children (2.9 percent), including high poverty places that have rates only slightly higher than low poverty places. One interesting finding is that both high and advancing poverty places saw sizable increases in the number of graduates with a high school or associate's degree (18.5 percent and 14.3 percent, respectively). However, the two groups also have the slowest rates of growth in college graduates (both under 3.0 percent) compared to declining and low poverty places.

There are also significant differences in economic structure and change across the poverty typology groups, and this information is presented in Table 7. Compared to low poverty places, both the High Poverty and Advancing High Poverty Groups have significantly larger shares of employment in agriculture and mining (15.5 percent and 18.0 percent), educational services (9.1 percent and 9.0 percent), and public administration (5.5 percent and 4.8 percent). The findings indicate that poorer places are more dependent on natural resource extraction, may have larger student populations associated with educational services, and have a larger government presence. The role of direct government employment could be both cause, where certain types of government enterprises cause poverty (e.g., military bases or prisons), and effect, where poor places need more government services.

By contrast, high and advancing poverty places have much smaller shares of employment in manufacturing (15.1 percent and 12.7 percent) and trade (12.7 percent and 12.9 percent) than low poverty places. In fact, higher poverty places are much less specialized in many advanced services compared to low poverty places, especially in informational, financial, professional, and administrative services. Higher levels of manufacturing and advanced services employment may lead to lower poverty since these industries have historically paid better wages and benefits than other sectors (Partridge and Rickman 2006). In general, the results of this analysis are consistent with those found in the poverty literature. One anomaly is that higher trade sector employment is associated with low poverty places, although this finding may reflect the presence of regional trade centers in larger, more urban places that make up the Low Poverty Group.

Differences in economic change between the poverty typology groups give some conflicting results. Apart from description an adequate empirical explanation of these differences is beyond the scope of this article. However, some observations can be made regarding economic restructuring by comparing the Low Poverty Group to the High Poverty and Advancing High Poverty Groups. Poorer places generally saw large declines in agriculture and mining, slow declines in manufacturing and trade, slow growth in services, and relatively fast growth in transportation, communication, and utilities. An interesting finding is that although low poverty places have higher rates of manufacturing employment, these places also saw the largest declines since 1980 (–7.4 percent). It appears that losses in manufacturing are offset by growth in services, finance, insurance, real estate, and construction—all sectors where poor places experienced very slow growth. These findings indicate that poor places are undergoing a different type of economic restructuring than more wealthy places.

Figure 2
Poverty Typology Groups by U.S. Department of Agriculture Persistent Poverty Counties for N = 34,908 Minor Civil Divisions from 1980 to 2000



Source: U.S. Census Bureau.
Note: USDA = U.S. Department of Agriculture.

Comparison to Other Typologies

To determine whether a more detailed typology enhances our understanding of place-based poverty, the poverty groups identified in this analysis are compared to the USDA Persistent Poverty County Codes. To make the typologies similar across time, the USDA typology was replicated by defining persistently poor counties as those with poverty rates of 20 percent or more in 1980, 1990, and 2000. An overlay of the two typologies is presented in Figure 2. In terms of geographic coverage, only 46.6 percent of places in the High Poverty Group fell within USDA's Persistent Poverty Counties. In terms of covering poor persons, however, the USDA typology includes 61.3 percent of the poor identified in high poverty places. This indicates that while the new typology includes many more geographic areas than the USDA typology, both tend to cover where the majority of poor people live. Furthermore, only 17.9 percent of places in the Advancing High Poverty Group are captured by USDA's typology—although the by definition the USDA typology excludes these areas. In other words, the new typology seems to identify poor places with relatively smaller populations and those that have experienced sizable poverty increases over time.

The greatest similarity between high poverty places and persistent poverty counties occurs in the Southern and Southwestern states, which have higher levels of poverty compared to the rest of the nation. Over 75 percent of high poverty places fell in persistently poor counties in Alabama, Georgia, Kentucky, Louisiana, Mississippi, and New Mexico. However, the new typology identified many poor places that are not picked up by the USDA typology, especially in the Midwestern and Northern states with historically low poverty rates. Less than 10 percent of poor places fell in persistent poverty counties in Idaho, Nebraska, New York, and Ohio. Furthermore, although several states have significant numbers of poor places, not one persistent poverty county is identified by USDA in Kansas, Maine, Michigan, Minnesota, and Nevada. It is clear that the new typology does better at identifying poor places not covered by the USDA typology in low poverty states. However, in high poverty states both typologies identify roughly the same poor areas.

Discussion and Conclusion

In short, the substantial literature on poverty demonstrates that certain types of geographic, demographic, and economic characteristics affect local poverty rates. However, there have been almost no empirical studies specifically looking at the geography of American poverty across space and time, especially at subcounty geographies (Irwin 2007; Lobao and Hooks 2007). This analysis develops a place-based typology of poverty over time to address this key gap in the existing poverty literature.

First, the results show that subcounty places of persistently high poverty exist in the United States over time. The analysis classified over 3,000 places into the High Poverty Group, which had poverty rates of nearly 20 percent above the national average going back to 1980. These persistent high poverty places account for nearly 11 percent of the nation's poor. Most of these places have populations just over 4,000 people, most live in rural areas, and most are located in the Southern and Southwestern states. However, less than 50 percent of places in the High Poverty Group fall within USDA's Persistent Poverty Counties.

Second, the results show that some places moved into and out of high poverty during the past 20 years. The Advancing High Poverty Group consists of nearly

1,500 places that saw their poverty rates jump from 4 percent to nearly 14 percent above the national average between 1980 and 2000. These places are larger and more urban than high poverty places but saw almost no population growth during the past two decades. Although worsening poverty places contain just over 12 percent of the nation's poor, less than 20 percent are captured within USDA's Persistent Poverty Counties. By contrast, the 1,600 places in the Declining High Poverty Group saw poverty rates drop from nearly 20 percent above average in 1980 down to less than 4 percent by 2000. Located mainly in the upper Midwest, these places have very small and entirely rural populations with fewer than 500 people.

Third, the results show that correlates of poverty identified in the literature generally hold true across smaller geographic scales. In terms of demographic correlates, the High Poverty Group has higher rates of minorities, work disabilities, single-headed families, unemployment rates, and those with no high school education—all consistent with the poverty literature. The same results are found for places in the Advancing High Poverty Group, indicating the two groups share similar demographic conditions. In terms of economic structure correlates, the results are consistent with the literature finding that high poverty places have more employment in agriculture, natural resources, and government, while low poverty places have more employment in manufacturing and higher-skill services. In terms of economic restructuring, high poverty places saw slower declines in manufacturing and very little growth in services compared to low poverty places. This indicates poor places are undergoing a different type of economic restructuring than more wealthy places. However, not all findings are supported by the literature. High poverty places have more educational services jobs, which is likely associated with larger student populations that increase poverty rates, albeit temporarily for students. Low poverty places have more employment in the trade sector, although this finding may reflect the presence of larger regional trade centers.

Last, the results show that a new poverty typology enhances our understanding of place-based poverty over existing typologies. The new typology clearly shows the diversity of poverty in terms of its depth, direction, and distribution. In terms of depth, the typology identifies places based on the relative severity of poverty. For example, the typology distinguishes between above average poverty (e.g., 5 percent over the national average) and extreme poverty (e.g., 30 percent above average). This is needed to better understand where extreme poverty exists and what socioeconomic factors may explain its presence.

In terms of direction, the typology explicitly incorporates components of change to uniquely identify places that both moved into and out of high poverty. No existing poverty typology classifies areas in this manner. Understanding the dynamics of these places opens a new area of poverty research for social scientists. The results of this work may help poor places and governments develop effective strategies to ameliorate persistent poverty. More telling, however, is the finding that a sizable share of the nation's poor currently live in places experiencing large poverty increases. This indicates growth in the poor population is not just occurring in historically poor places; rather, it is also growing in new places that are fast becoming persistently poor.

In terms of distribution, the typology identifies many poor places that are "statistically invisible" using existing typologies. By using subcounty units, the new typology does a better job at identifying poor places in relatively low poverty states compared to the USDA typology. However, both typologies show a strong concentration of persistent poverty in the Southern and Southwestern states. The results also show that many advancing poverty places are developing in previously average and low poverty states—a worrying trend that may indicate the development of new persistent high poverty places. It also demonstrates that high poverty is highly localized and exists in nearly all states. In short, the typology developed here helps social scientists better understand the geography of American poverty over time.

Note

1. Cluster analysis was chosen over other methods, notably factor analysis, for several reasons (Kim and Mueller 1978; Loehlin 1992). Cluster analysis is the most appropriate method for creating a classification or typology, which is one of the main objectives of this analysis. Cluster analysis places very few assumptions on the data, whereas factor analysis assumes that the data must be factorable and correlated. Cluster analysis produces mutually exclusive groupings that can be used in regression-type procedures, such as logistic regression or discriminant function analysis, to statistically test the accuracy of the groupings. By contrast, factor analysis provides no such tests, and the overlapping nature of the factors prohibits the use of such procedures.

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