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Submitted Article

Place-Based Income Inequality Clusters in the Rural North Central Region, 1979–2009

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Abstract *This analysis identifies and describes clusters of persistently low and high income inequality for* N = *7,353 non-metropolitan block-groups in the western part of the North Central Region. Analysis finds more low inequality than high inequality places in the region, but there are also large numbers of rising inequality places. Lower inequality places are found to have poorer demographic and economic outcomes than higher inequality places, contrary to what is found in the literature. Lower inequality places are also found to be more specialized in traditional agricultural and industrial sectors, while higher inequality places are more specialized in higher skilled services industries.*

Key words: Income inequality, rural development, small area geographies, cluster analysis.

JEL Codes: I31, I32, R10.

Up until the 1980s, the United States experienced a period of rising incomes and relatively equal income distributions that began shortly after World War II (McGranahan). Over the past three decades, however, incomes have begun to level off and income distributions have become more unequal (Gottschalk and Smeeding; Moller, Alderson, and Nielsen). Even during the economic boom of the late 1990s, when Americans became more prosperous as a whole, income inequality remained high and actually increased (Hammond and Thompson). As a result of these trends, social scientists began to document the causes of rising income inequality. The bulk of this work has focused on national and state-level analyses, and the conclusions from these studies hold true across most states (Partridge, Rickman, and Levernier; Lynch). More recently, social scientists have begun to study income inequality at more localized levels, especially at the county-level (Levernier, Partridge, and Rickman 1998; Moller, Alderson, and Nielsen). However, few studies have been conducted at the subcounty scale for non-metropolitan areas (Wheeler and La Jeunesse).

There is a need to better understand the dynamics of non-metropolitan income inequality across subcounty geographies and multiple time periods. Previous research has clearly demonstrated that inequality and poverty persists in the United States across regions over time (Lobao; Lobao and Saenz; McLaughlin; Morrill; Partridge and Rickman 2005; Weber et al.). This body of work has demonstrated that inequality and poverty can be explained by differences in economic structures, individuals, natural resources, geography, and history. While the poverty literature has studied these dynamics at smaller subcounty geographies (Nizalov and Schmid; Peters), there have been only a handful of studies specifically looking at income inequality across these same geographic scales (Levy and Murnane; Jargowsky; Lobao and Hooks; Weber et al.; Wheeler and La Jeunesse). Further, the small number of existing studies focuses on metropolitan areas and neighborhoods. Understanding the dynamics of income inequality at the subcounty level is important because using larger geographic scales has been found to increase aggregation error, thus making many rural places statistically invisible and masking important trends (Wheeler and La Jeunesse).

The purpose of this analysis is to identify and describe clusters of persistent, low and high income inequality in rural areas, thus its focus is more exploratory than predictive. The first objective is to create a statistically valid typology of income inequality across time for subcounty places in the western part of the North Central Region (NCR-W). The second objective is to describe the demographic and economic characteristics of these places. This analysis fills a gap in the literature, by specifically examining income inequality across subcounty places over time in non-metropolitan areas, and it complements existing poverty research across the same geographic scales. The analysis is unique in terms of space, using subcounty-level census block-groups to approximate non-metropolitan places to prevent potential aggregation error in the analysis. It is unique in terms of time, using census data from 1979, 1989, 1999, and 2009 to offer a long-term yet current look at income inequality trends. It is unique in terms of methods, using cluster analysis to identify statistically clusters of persistent income inequality.

Another reason why there is a need to better understand income inequality is its increase both in the NCR-W and the United States over the past thirty years. While poverty rates have generally declined over this period (save for modest increases between 1999 and 2009), rates of income inequality have generally increased (Moller, Alderson, and Nielsen). In addition, growth in inequality over the past three decades varies greatly across states and regions. States in the NCR-W are unique in that inequality is low and grew slowly over this period. By contrast, states in the north-east and the west experienced some of the fastest growth in inequality, while southern states have high rates of inequality that actually declined over the last thirty years. This suggests that the causes of poverty and inequality likely differ and need to be studied separately across regions.

One weakness of this analysis is that the geographic scope is limited to the seven states of the NCR-W. However, the results can be of use in understanding rural income inequality more broadly since the region is generally similar to the non-metropolitan population in the United States; and because it also contains some of the most rural places in the nation (refer to table 1 for a detailed comparison). Further, the NCR-W region presents a unique empirical case study of low inequality in the United States over the past thirty years. States in the region have the slowest increases in inequality while also having the lowest absolute levels of

Table 1 Socioeconomic characteristics of non-metropolitan areas in the NCR-W and the United States for 2009

Characteristic	*NCR-W*	*United States*	
Population (millions)	6.5	49.4	
Median Age (years)	40.4	39.5	
Population 65 years and older (%)	17.0	15.5	a
Population white and not Hispanic (%)	92.9	84.6	a
Population Hispanic of any race (%)	4.5	6.7	a
Population with a high school degree (%)	37.4	37.1	
Population with a college degree or higher (%)	17.9	17.1	
Labor force participation (%)	65.0	59.9	a
Unemployment (%)	5.3	7.4	a
Median household income (nom $)	41,884	40,494	a
Agriculture and natural resources (%)	7.7	5.5	a
Construction (%)	7.1	8.2	
Manufacturing (%)	15.5	14.8	
Wholesale trade (%)	3.0	2.6	
Retail trade (%)	11.8	12.0	
Transportation and warehousing (%)	5.3	5.2	
Information services (%)	1.6	1.5	
Finance, insurance, real estate, rental (%)	4.5	4.4	
Professional and administrative services (%)	4.8	5.9	
Education, healthcare, social assistance (%)	22.8	22.0	
Arts, entertainment, accommodation, food services (%)	7.3	8.2	
Other services (%)	4.5	4.7	
Public administration (%)	4.1	5.1	

Source: U.S. Census Bureau (2005–09 American Communities Survey).
[a]Significant difference at p 0.01.

inequality in the nation. Understanding the dynamics of this region is important for informing public policy aimed at promoting social and economic integration, of which inequality is one indicator. Thus the results can then be used to inform rural development policy at the state and federal levels.

Previous Research on Inequality

A number of studies have demonstrated that place matters in understanding inequality, and a comprehensive review of this work is presented by Weber et al.. The majority of these studies take a labor market approach to understanding inequality and poverty, which incorporates both individual and structural approaches within a spatial context (Cotter; Lobao, Hooks, and Tickamyer; McLaughlin). These studies generally attempt to understand county-level inequality in terms of different demographic characteristics, family structure components, geographic locations, industrial compositions, and a host of other labor market factors (Crandall and Weber; Levernier, Partridge, and Rickman 1998, 2000; Lobao, Rulli, and Brown; Moller, Alderson, and Nielsen; Partridge and Rickman 2006, 2007).

In terms of geography, most studies of inequality use states as the unit of analysis (Lynch 2003; Partridge and Rickman 2007). However, a number of studies have examined income inequality at the county level

(Hammond and Thompson; McLaughlin; Moller, Alderson, and Nielsen). In many ways, counties are ideal units of analysis to study inequality 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 inequality and various socioeconomic factors hold across geographic scales (Lobao and Hooks; Irwin). Analysis of poverty at smaller geographies is fairly well documented in the literature, specifically looking at poverty across block-groups (Nizalov and Schmid), minor civil divisions (Peters), and census tracts (Crandall and Weber; Jargowsky).

However, there are nearly no studies specifically looking at income inequality at smaller geographies. The only study to examine subcounty inequality to date is by Wheeler and La Jeunesse, who look at inequality by block-groups in metropolitan areas between 1980 and 2000. The authors argue that using block-groups reveals important differences among neighborhoods in metropolitan areas. They found greater levels of income inequality when using smaller geographic scales, and smaller levels when using larger scales. They also found that overall levels of income inequality in large metropolitan areas are driven by variation within block-groups, rather than variation between them. They conclude that larger geographic scales result in aggregation errors that mask high inequality neighborhoods, making them statistically invisible.

Several studies have also explicitly incorporated spatial statistics into their analyses (Crandall and Weber; Moller, Alderson, and Nielsen; Partridge and Rickman 2005, 2006, 2007). This work finds that high inequality counties are spatially clustered, and high adjacent inequality exerts a strong positive effect on local inequality. Moller, Alderson, and Nielsen examine county income inequality between 1970 and 2000, and find that inequality is concentrated in the southern United States, Appalachia, the south-west, and the northern Great Plains—areas that all have high and persistent poverty rates. However, they also found pockets of high inequality in low poverty areas, especially in the western coastal states and parts of New England.

In terms of demographic structure, the literature unanimously supports the finding that higher levels of educational attainment reduce inequality, especially high school and Associate's degrees. A strong relationship is also found between greater numbers of single-headed families with children and high local inequality, especially among those headed by females. The impact that minority populations have on inequality is less clear in the literature. Most studies show that larger populations of non-African American minorities tend to increase local inequality (Levernier, Partridge, and Rickman 1998; Moller, Alderson, and Nielsen). However, the findings for African American populations are mixed. Nation-scale studies show that African American populations are associated with lower rates of inequality (Levernier, Partridge, and Rickman 2000; Moller, Alderson, and Nielsen), while non-metropolitan studies show increases in inequality (Lobao, Rulli, and Brown; McLaughlin; Levernier, Partridge, and Rickman 1998). Most of the analyses also look at the effect of age structure, and generally find that persons under the age of twenty-four tend to increase local inequality, while persons over the age of sixty-four tend to reduce inequality.

In terms of economic conditions, one of the strongest findings is that current inequality is highly dependent on previous inequality—indicating that inequality is path dependent (Moller, Alderson, and Nielsen). The majority of studies show that increases in labor force participation rates leads to lower inequality rates at the county level, especially for women. As one would expect, the literature also shows that higher unemployment rates lead to higher local inequality, and this effect is particularly strong for male unemployment. Several analyses include employment growth and industrial restructuring in their models explaining inequality (Crandall and Weber; Levernier, Partridge, and Rickman 1998, 2000; Partridge and Rickman 2005, 2007; Swaminathan and Findes). The findings demonstrate that employment growth strongly reduces local inequality, especially when counties are near metropolitan areas. Counties experiencing industrial structuring are more likely to have higher inequality, as are counties with a less diversified industrial base.

A number of studies include industry employment variables to model local economic structure (Levernier, Partridge, and Rickman; McLaughlin; Moller, Alderson, and Nielsen). The findings show that employment in traditional industrial sectors, such as manufacturing and mining, tends to reduce local inequality. It is argued that these industries, owing to their history of unionization, offer better wages and benefits that reduce inequality. Employment in communication services, health services, and professional services is also found to be associated with lower rates of inequality. These higher-skill industries tend to pay higher wages and better benefits. By contrast, the literature also shows that employment in agriculture, trade, business services, and personal services increases local inequality. Since these industries tend to rely on more part-time or temporary labor arrangements, often for lower pay, it is argued that they result in higher inequality.

Conceptually the link between industrial restructuring and inequality is rooted in Bell's argument that modern capitalist societies are undergoing a shift away from a primarily goods-producing industrial economy toward a more services-producing post-industrial economy. The social polarization thesis, based in part on Bell's work, argues that change in economic structure from industrial to post-industrial has increased inequality (Hamnett; Sassen). According to this view, the shift toward a post-industrial economy has increased the number of higher-skill and higher-wage jobs in the financial, business, and professional services sectors. At the same time, however, this has been paralleled by growth in relatively lower-skilled and lower-wage services jobs that support post-industrial industries and serve members of this growing professional and managerial class. These trends, along with declines in industrial goods-producing sectors, are argued to have reduced middle-skilled and middle-wage jobs and results in growing polarization of incomes.

Data and Methods

In order to better understand persistent low and high income inequality over time, this analysis uses a unique set of spatial data from the 1980, 1990, and 2000 Decennial Census, and the 2005–09 American Communities Survey (ACS). Although ACS data are not point-in-time estimates, they are the only source of income distribution data at the county and subcounty levels. The ACS has replaced the long-form Decennial Census, and there are some important differences between the two that should be noted. First, ACS data represent average values for each year during 2005–09, rather than point-in-time estimates. Second, income and employment status are for the previous twelve-month period, rather than for the previous calendar year. Third, standard errors for the ACS tend to be higher for smaller geographies than was the case in previous census periods using the long form. However, analysis of the standard errors finds no estimate whose coefficient of variation exceeds 25 percent, indicating adequate data quality.

The units of analysis are non-metropolitan census block-groups in the NCR-W, which includes Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota. Block-groups are the smallest geographic unit for which the census publishes data. Since these units are delineated by local partners and the Census Bureau, block-groups tend to represent distinct places or neighborhoods. Block-group geographies change with each census, and the data in this analysis are geographically corrected to the 2000 census geographies to permit comparisons over time. Block-groups with low populations or missing data in any time period are dropped from the analysis ($N = 34$), which results in $N = 7{,}353$ non-metropolitan block-groups in the NCR-W for analysis.

Income inequality is measured using Gini coefficients that are calculated across fourteen income categories in each block-group using census data for 1979, 1989, 1999, and 2009. To correct for inflation and to equalize the number of categories for analysis, the income categories for previous periods are combined to approximate 2009 income levels based on the consumer price index. Aggregated income within each household income category is used to calculate the Gini coefficients (G).[1] The formula for G is presented in equation 1, where σX is the cumulative distribution of equality values under a Lorenz curve, σY is the cumulative distribution of households by income categories, and N is the number of income categories. G coefficients are standardized to a mean of zero and standard deviation of one for ease of interpretation. Standardized G, $(s)G$, is used to create the income inequality typology based on sample means and standard deviations.

$$G = \left| 1 - \sum_{i=0}^{n} (\sigma Y_i + \sigma Y_{i-1})(\sigma X_i - \sigma X_{i-1}) \right|. \qquad (1)$$

To achieve the first objective of the study, hierarchical agglomerative cluster analysis is used to create a statistically valid typology of income inequality across time for subcounty places in the rural NCR-W area. Agglomerative cluster analysis is a multivariate statistical procedure that

[1] *To estimate aggregated income the midpoint of each income category is calculated and multiplied by the number of households. However, the 1980 census and the 2005–09 ACS did not report aggregate income at the top income category. To do this, the sum of aggregated income using category midpoints is calculated excluding the top-coded category. This sum is compared to total aggregate income reported by the census. If the difference between the two is greater than the product of the top income category by the number of households, then the difference is used instead of the product.*

starts with data containing information about a sample of entities and attempts to reorganize them into relatively homogeneous groups, primarily to create classifications and typologies (Everitt, Landau, and Leese). In this analysis, squared Euclidean distance is used to measure distances between clusters and block-groups based on (s)G for 1979, 1989, 1999, and 2009. The formula for squared Euclidean distance is based on the Minkowski generalized distance metric and is given in equation 2, where d_{ij} is the distance between block-groups i and j, x_{ik} is the value of the kth standardized G for the ith block-group, and x_{jk} is the value of the kth standardized G for the jth block-group (Everitt, Landau, and Leese).

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

Clusters and block-groups 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, E, until all block-groups are grouped into one cluster. The formula for Ward's method is presented in equation 3, where $\bar{x}_{m.k}$ is the mean of the mth cluster for the kth standardized G, and $x_{ml,k}$ is the score on the kth standardized G ($k = 1 \ldots p$) for the lth block-group ($l = 1 \ldots n_m$) in the mth cluster ($m = 1 \ldots g$).

$$E = \sum_{m=1}^{g} \left(\sum_{l=1}^{n_m} \sum_{k=1}^{p} \left(x_{ml,k} - \bar{x}_{m,k} \right)^2 \right) \tag{3}$$

where

$$\bar{x}_{m,k} = \left(\frac{1}{n_m} \right) \sum\nolimits_{l=1}^{n_m} x_{ml,k}.$$

To achieve the second objective, Scheffe's multiple comparison test is used to identify significant differences between the clusters across key demographic and economic characteristics. Indicators for each block-group are taken from census data for 1979 and 2009, and are by place of residence. Descriptive statistics for all variables used in the analysis are presented in table 2. Scheffe's test is given in equation 4, where $\bar{x}$ are the means, s^2 is the mean of squared errors, n is the number of cases, k is the number of comparisons, and F is the critical value at a given alpha level and degrees of freedom.

$$S = \frac{\bar{x}_i - \bar{x}_j}{\sqrt{s^2 \left(\frac{1}{n_i} + \frac{1}{n_j} \right)}} \geq \sqrt{(k-1) F_{(\alpha; k-1, n-k)}} \tag{4}$$

Given that the main focus of the analysis is exploratory rather than predictive, cluster analysis with mean difference tests are used instead of regression analysis for several reasons. First, cluster analysis avoids

Table 2 Descriptive statistics in the non-metropolitan NCR-W, 1979–2009

Gini scores	*Mean*	*SD*
1979	0.280	0.080
1989	0.409	0.091
1999	0.416	0.095
2009	0.549	0.094
2009	***Mean***	***SD***
Population (number)	1034.85	531.18
Metropolitan adjacency (%)	0.359	0.480
Minority population (%)	9.188	14.390
Single-headed families (%)	19.048	13.599
No high school degree (%)	13.852	9.165
College degree or higher (%)	18.032	10.585
Labor force participation (%)	79.079	199.927
0–99 percent of poverty (%)	13.501	11.323
100–199 percent of poverty (%)	21.655	10.436
Median household income (nom $)	43,590	13,986
Agriculture and natural resources (%)	8.247	10.051
Construction (%)	7.303	5.389
Manufacturing (%)	14.940	10.121
Trade (%)	14.510	7.430
Transportation and utilities (%)	5.370	4.710
Information services (%)	1.592	2.350
Finance, insurance, real estate, rental (%)	4.468	4.034
Professional, administrative services (%)	4.759	4.425
Education, health, social services (%)	22.862	9.360
Leisure and other services (%)	11.527	7.511
Change during 1979–2009	***Mean***	***SD***
Population (%)	1.448	47.151
Minority population (%)	5.259	10.502
Single-headed families (%)	8.840	12.250
No high school degree (%)	−21.604	10.097
College degree or higher (%)	6.825	8.480
Labor force participation (%)	8.660	198.874
0–99 percent of poverty (%)	−0.309	11.493
100–199 percent of poverty (%)	−0.317	11.760
Median household income (%, nom $)	212.476	89.757
Agriculture and natural resources (%)	−8.810	10.471
Construction (%)	0.956	5.630
Manufacturing (%)	−1.508	9.656
Trade (%)	−5.765	8.344
Transportation, communication, utilities (%)	0.597	5.372
Finance, insurance, real estate (%)	0.799	4.221
Professional services (%)	−0.537	3.426
Education, health, social services (%)	5.993	8.978
Leisure, business, other services (%)	7.732	7.863

Note: Leisure industry includes arts, entertainment, recreation, accommodation, and food services.
Source: U.S. Census Bureau (1980 Census SF3 and 2005–09 American Communities Survey).

endogeneity issues which would likely be present when predicting 1979–2009 inequality using either 1979 or 2009 values for the predictors. Cluster analysis seeks to uncover patterns in the data, rather than seeking cause-and-effect. Second, cluster analysis avoids the problem of using arbitrary criteria to identify high or low inequality places. Instead the technique bases the criteria on the unique distribution of the data in each time period. Third, cluster analysis takes into account the relative degree of inequality by distinguishing between extreme and above average values. The technique is a form of sensitivity analysis, again based on the unique distribution of the data. Fourth, cluster analysis explicitly incorporates components of change, which permits identification of places that moved in or out of inequality over time.

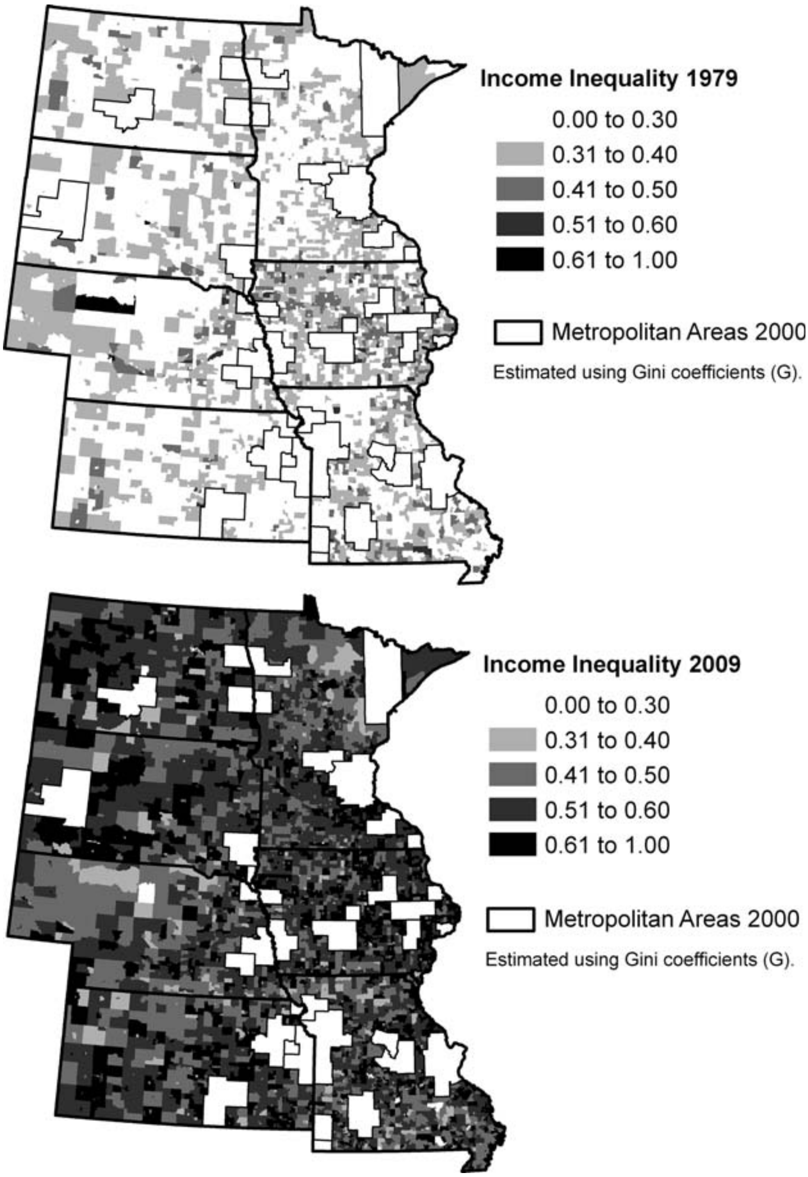
Results

One reason why there is a need to better understand income inequality in the NCR-W is its rapid increase across rural places over the past thirty years. In 1979 the vast majority of rural places in the NCR-W had low rates of income inequality, with 64.9 percent having Gini coefficients of 0.30 or less and 27.2 percent having scores between 0.31 and 0.40. Only 1.1 percent of places had high rates of inequality with Gini coefficients over 0.50. By 2009 this distribution had flipped as income inequality increased in nearly all places. Now, only 5.3 percent of places have low rates of income equality with Gini coefficients of 0.40 or less. Higher levels of inequality are more widespread, with 40.4 percent of places having Gini coefficients of 0.51 to 0.60, and 28.9 percent having scores over 0.60 (refer to figure 1).

The results of the cluster analysis indicate that the $N = 7{,}353$ block-groups can be clustered into five groups based on their standardized Gini coefficients, accounting for nearly 50 percent ($R^2 = 0.490$) of the variance in the data (compared to an expected value of $(E)R^2 = 0.638$ for an optimal solution). Based on the information presented in table 3, the results indicate the presence of either 4 or 5 clusters based on the loss of information diagnostics. The slope and semipartial R^2 statistics show a large loss of information (indicated by jumps) at stages 4 and 3, and taking the previous stage indicates 5 to 4 clusters. A jump in pseudo t^2 at stage 3 indicates a 4 cluster solution. Relatively high values of pseudo F also indicate the presence of 5 or 4 clusters. The 5 cluster solution is chosen because it produces more informative groupings than the 4 cluster solution. In addition, cluster analysis was run using other agglomerative methods (including average linkage, centroid method, and Gower's median method), and these generally produced similar cluster groupings.

The *low inequality cluster* consists of 1,578 block-groups that have very low rates of income equality between 1979 and 2009. Except for 1979, places in this cluster have Gini coefficients that are more than one standard score below the mean for each period. North Dakota (27.5 percent) and Nebraska (27.0 percent) have the largest share of block-groups in this cluster, followed by South Dakota (24.8 percent), Missouri (25.1 percent), Minnesota (21.9 percent), Kansas (18.6 percent), and Iowa (14.0 percent). The *falling inequality cluster* experienced declining rates of inequality, going from very high inequality in 1979 (mean $(s)G = 1.420$) to nearly

Figure 1 Income inequality in the NCR-W, 1979–2009



Source: U.S. Census Bureau (1980 Census SF3 and 2005–09 American Communities Survey).

average rates of inequality by 2009 (mean $(s)G = 0.335$). Iowa (24.3 percent) has the largest share of these 1,578 block-groups, followed by North Dakota (14.7 percent), Nebraska (13.7 percent), Missouri (13.1 percent), Kansas (12.7 percent), and Minnesota (11.1 percent). Table 4 and figure 2 present the means and geographic distributions for these clusters.

By contrast, the 1,974 block-groups in the *rising inequality cluster* experienced increases in income inequality over this period. Inequality rose from average levels in 1979 (mean $(s)G = -0.191$) to relatively high levels of inequality by 2009 (mean $(s)G = 0.776$). South Dakota (31.4 percent) and Kansas (30.1 percent) have the largest shares of rising inequality places, followed by Iowa (27.0 percent), Minnesota (26.8 percent),

Table 3 Results of hierarchical agglomerative cluster analysis in the non-metropolitan NCR-W, 1979–2009

Clusters	*Distance*	*Slope*	R^2	$(E)R^2$	$(sp)R^2$	$(p)F$	$(p)t^2$
15	0.009	14.533	0.662	0.791	0.009	1027.214	274.075
14	0.010	19.913	0.652	0.784	0.010	1057.007	216.893
13	0.010	0.017	0.642	0.776	0.010	1094.814	94.718
12	0.011	3.732	0.631	0.767	0.011	1140.667	237.198
11	0.012	15.074	0.619	0.756	0.012	1190.849	250.185
10	0.016	30.148	0.603	0.744	0.016	1237.294	313.078
9	0.017	9.042	0.585	0.730	0.017	1295.074	357.272
8	0.019	8.622	0.566	0.714	0.019	1369.868	460.435
7	0.024	28.257	0.542	0.694	0.024	1448.745	400.163
6	0.024	0.252	0.518	0.669	0.024	1576.823	409.450
5	0.028	14.874	0.490	0.638	0.028	1762.612	577.706
4	0.046	63.402	0.444	0.595	0.046	1955.986	479.632
3	0.067	47.562	0.377	0.530	0.067	2219.550	1128.083
2	0.078	16.066	0.298	0.410	0.078	3124.698	823.500
1	0.298	281.131	0.000	0.000	0.298	n.a.	3124.698

Note: Cluster variables include standardized Gini coefficients for 1979, 1989, 1999, and 2009. N = 7,353 block-groups are clustered using squared Euclidean distance and Ward's method. n.a. Not applicable.

Table 4 Descriptive statistics of income inequality clusters in the non-metropolitan NCR-W, 1979–2009

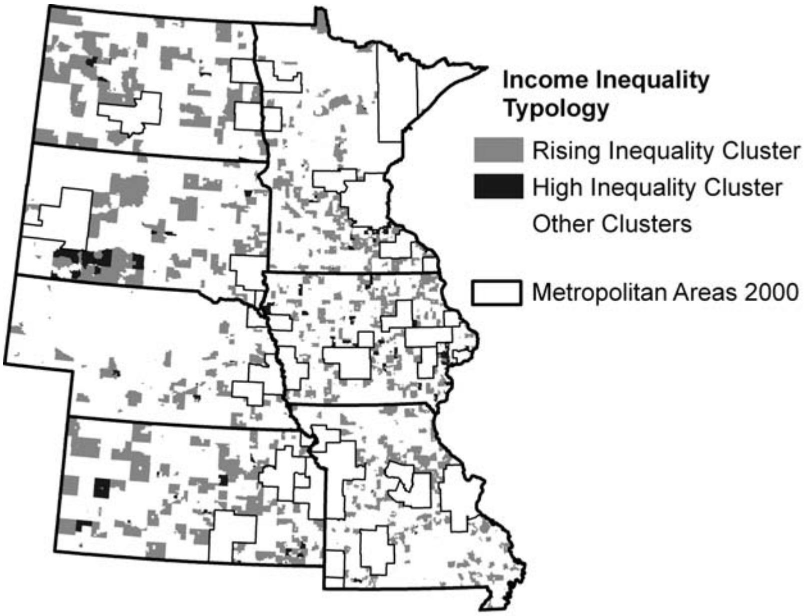
		Gini 1979 standardized		*Gini 1989 standardized*		*Gini 1999 standardized*		*Gini 2009 standardized*	
Inequality clusters	*N*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Low	1,578	−0.380	0.815	−0.945	0.595	−1.047	0.564	−1.095	0.650
Falling	1,091	1.420	0.715	0.612	0.822	0.433	0.855	0.335	0.720
Average	2,462	−0.381	0.662	−0.121	0.796	−0.217	0.583	−0.261	0.588
Rising	1,974	−0.191	0.650	0.353	0.826	0.599	0.754	0.776	0.661
High	248	1.469	1.340	1.716	1.141	2.147	0.885	1.913	0.726

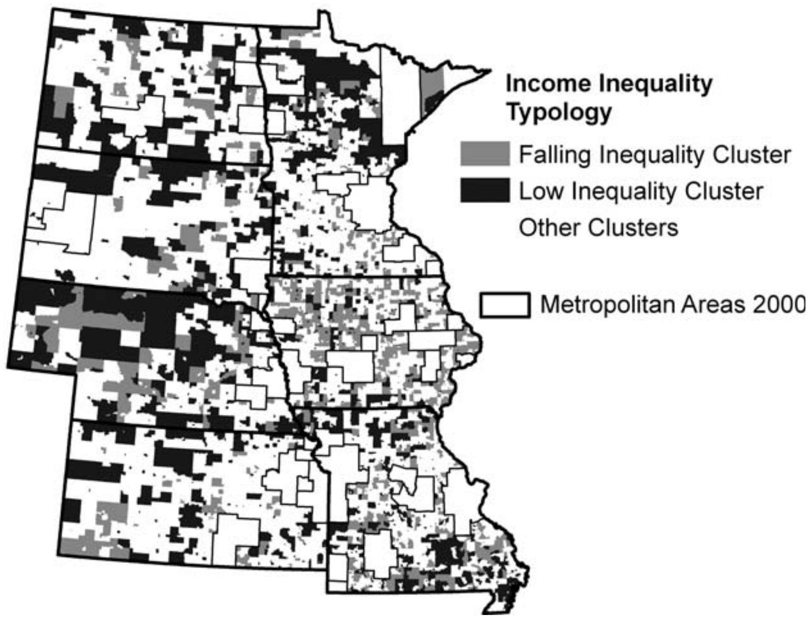
Source: U.S. Census Bureau (1980–2000 Census SF3 and 2005–09 American Communities Survey).

North Dakota (25.3 percent), Missouri (25.2 percent), and Nebraska (25.3 percent). Lastly the *high inequality cluster* contained only a handful of block-groups ($N = 248$) that have experienced persistently high income inequality since 1979 (roughly 1.5 to 2.0 standard scores above the mean). States with the largest concentrations of high inequality places are South Dakota (4.7 percent), Kansas (4.4 percent), Iowa (4.2 percent), North Dakota (3.9 percent), Nebraska (3.3 percent), Minnesota (3.1 percent), and Missouri (at only 1.7 percent). Refer to table 4 and figure 2.

In order to better understand key demographic and economic differences between the clusters, tables 5 and 6 present the cluster means along with the results of Scheffe's test. Compared to the higher inequality clusters, the *low inequality cluster* has more single-headed families, more people without a high school education, fewer college graduates, lower labor force participation rates, higher levels of poverty and near poverty

Figure 2 Inequality clusters in the NCR-W, 1979–2009





Source: U.S. Census Bureau (1980 Census SF3 and 2005–09 American Communities Survey).

(100–199 percent), and lower median household incomes. Since 1979, low inequality places saw declining populations, growth in single-headed families, faster declines in those without a high school degree, slower increases in college graduates, faster increases in poverty, and slower growth in median incomes. In terms of employment characteristics, low inequality places have more employment in the agriculture, natural resources, and construction industries; and less employment in higher skill services industries like finance, professional services, education, and healthcare. Manufacturing employment is significantly lower compared to most other clusters (except the high inequality cluster). Since 1979, employment in agriculture and professional services has dropped faster than in other clusters, while manufacturing employment has experienced much slower declines.

By contrast, places in the *high inequality cluster* are more educated, more wealthy, and more economically engaged in higher skilled services. High inequality places have lower numbers and slower rates of growth in single-headed families and those without a high school education. About one-third of the population has a bachelor's degree or higher, and this rate has increased since 1979. Labor force participation rates are much higher than lower inequality places; and median household income is over $65,000 and has the fastest growth rate of all clusters. There are fewer numbers of people living in poverty or near poverty, and rates of near poverty fell faster than in all other clusters.

In terms of industry structure, high inequality places have more employment and higher growth in finance, insurance, real estate, professional, business, and administrative services than low inequality clusters. Employment in education, health, and social services is also higher, but growth rates are average. Conversely employment in more traditional rural industries is smaller, especially in agriculture, construction, and manufacturing. While the high inequality cluster experienced some of the fastest declines in manufacturing since 1979, this cluster also experienced some of the slowest declines in agriculture.

While differences between the low and high inequality clusters are readily apparent, the differences are more nuanced when looking at characteristics of the *rising inequality cluster*. The rising and high inequality clusters share many of the same differences compared to lower inequality clusters, such as fewer single-headed families, more people without a high school degree, more college-educated persons, high labor force participation, lower rates of poverty and near poverty, and higher median incomes. However, there are some important differences between the two. Places in the rising inequality cluster have the lowest populations of all clusters, but these places had modest growth since 1979. Minority populations, being nonwhite or Hispanic of any race, are higher and have grown faster over the past decades than in the lower inequality clusters. One puzzling series of findings shows that single-headed families, persons with no high school degree, and poverty rates are actually higher in rising inequality places than falling inequality places. However, these same indicators are all lower compared to low inequality places.

Similar to the high inequality cluster, we find that rising inequality places have lower employment in agriculture and construction, and higher employment in more skilled services industries like finance and professional services. However, this cluster is more specialized in manufacturing compared to both low and high inequality clusters. Professional services employment is higher than in low inequality places, but is statistically the same compared to falling inequality places. Employment in education and health services is the same between rising and low inequality places, but is higher than that found in falling inequality places. Rising inequality places also have less employment in transportation and utilities, faster declines in trade employment, and slower declines in professional services compared to lower inequality places.

Table 5 Demographic characteristics of income inequality clusters in the non-metropolitan NCR-W, 1979–2009

Base population in 2009	*Low inequality*	*Falling inequality*	*Average inequality*	*Rising inequality*	*High inequality*
Population (number)	1,052$^{\text{RH}}$	1,028	1,059$^{\text{RH}}$	988$^{\text{LARH}}$	1,090
Metropolitan adjacency (%)	0.321$^{\text{A}}$	0.366	0.385$^{\text{L}}$	0.361	0.318
Minority population (%)	8.373$^{\text{R}}$	7.638$^{\text{R}}$	9.155$^{\text{R}}$	10.607$^{\text{LFA}}$	10.279
Single-headed families (%)	20.519$^{\text{FRH}}$	15.740$^{\text{LARH}}$	20.499$^{\text{FRH}}$	18.737$^{\text{LFAH}}$	12.143$^{\text{LFAR}}$
No high school degree (%)	16.175$^{\text{FARH}}$	11.751$^{\text{LARH}}$	14.575$^{\text{LFRH}}$	12.947$^{\text{LFAH}}$	8.450$^{\text{LFAR}}$
College degree or higher (%)	14.571$^{\text{FARH}}$	19.310$^{\text{LAH}}$	16.594$^{\text{LFRH}}$	19.921$^{\text{LAH}}$	33.511$^{\text{LFAR}}$
Labor force participation (%)	69.592$^{\text{FARH}}$	77.382$^{\text{LH}}$	75.941$^{\text{LRH}}$	80.393$^{\text{LAH}}$	90.572$^{\text{LFAR}}$
0–99 percent of poverty (%)	16.117$^{\text{FARH}}$	9.962$^{\text{LAR}}$	14.379$^{\text{LFRH}}$	12.791$^{\text{LFAH}}$	7.833$^{\text{LAR}}$
100–199 percent of poverty (%)	25.792$^{\text{FARH}}$	19.595$^{\text{LAH}}$	22.816$^{\text{LFRH}}$	19.417$^{\text{LAH}}$	10.603$^{\text{LFAR}}$
Median household income (nom $)	36,129$^{\text{FARH}}$	49,074$^{\text{LAH}}$	40,613$^{\text{LFRH}}$	47,672$^{\text{LAH}}$	65,486$^{\text{LFAR}}$
Change from 1979–2009					
Population (%)	−4.823$^{\text{FARH}}$	5.572$^{\text{LH}}$	0.514$^{\text{LH}}$	2.047$^{\text{LH}}$	28.989$^{\text{LFAR}}$
Minority population (%)	5.079	4.359$^{\text{R}}$	5.419	5.937$^{\text{FH}}$	3.545$^{\text{R}}$
Single-headed families (%)	10.491$^{\text{FRH}}$	7.634$^{\text{LAH}}$	9.799$^{\text{FRH}}$	7.644$^{\text{LAH}}$	3.481$^{\text{LFAR}}$
No high school degree (%)	−23.567$^{\text{FARH}}$	−19.955$^{\text{LAH}}$	−22.016$^{\text{LFRH}}$	−21.015$^{\text{LAH}}$	−16.774$^{\text{LFAR}}$
College degree or higher (%)	5.132$^{\text{FARH}}$	7.274$^{\text{LAH}}$	5.968$^{\text{LFRH}}$	8.011$^{\text{LAH}}$	14.723$^{\text{LFAR}}$
Labor force participation (%)	6.225	3.194	6.791	6.676	8.213
0–99 percent of poverty (%)	−0.034$^{\text{F}}$	−1.991$^{\text{LAR}}$	0.136$^{\text{F}}$	−0.062$^{\text{F}}$	−2.207
100–199 percent of poverty (%)	1.295$^{\text{FRH}}$	−0.250$^{\text{LRH}}$	0.277$^{\text{RH}}$	−1.645$^{\text{LFAH}}$	−6.078$^{\text{LFAR}}$
Median household income (%, nom $)	199.331$^{\text{RH}}$	205.431$^{\text{RH}}$	204.574$^{\text{RH}}$	231.831$^{\text{LFAH}}$	259.851$^{\text{LFAR}}$

Note: Scheffe's test indicates significant differences at $p < 0.05$ between low inequality (L), falling inequality (F), average inequality (A), rising inequality (R), and high inequality (H) clusters.
Source: U.S. Census Bureau (1980 Census SF3 and 2005–09 American Communities Survey).

Table 6 Employment characteristics of income inequality clusters in the non-metropolitan NCR-W, 1979–2009

Employed population in 2009	*Low inequality*	*Falling inequality*	*Average inequality*	*Rising inequality*	*High inequality*
Agriculture and natural resources (%)	9.860^{ARH}	9.200^{ARH}	7.964^{LF}	7.052^{LF}	6.091^{LF}
Construction (%)	7.609^{RH}	7.550^{H}	7.365^{H}	7.017^{L}	5.913^{LFA}
Manufacturing (%)	13.804^{FARH}	15.749^{LH}	15.336^{LH}	15.368^{LH}	11.245^{LFAR}
Trade (%)	14.559	14.004	14.773	14.443	14.336
Transportation and utilities (%)	5.733^{R}	5.737^{R}	5.356	4.925^{LF}	5.130
Information services (%)	1.555	1.487	1.568	1.692	1.724
Finance, insurance, real estate, rental (%)	4.198^{RH}	4.443^{H}	4.296^{RH}	4.705^{LAH}	6.150^{LFAR}
Professional and administrative services (%)	4.092^{FARH}	4.926^{LH}	4.543^{LRH}	5.300^{LA}	6.122^{LFA}
Education, health, social services (%)	22.582^{H}	21.915^{RH}	22.685^{H}	23.467^{FH}	25.775^{LFAR}
Leisure and other services (%)	11.693^{F}	10.496^{LAR}	11.866^{F}	11.635^{F}	10.790
Change from 1979 to 2009					
Agriculture and natural resources (%)	−9.756^{FARH}	−11.053^{LARH}	−8.689^{LFR}	−7.146^{LFA}	−7.351^{LF}
Construction (%)	1.048	1.219	1.017	0.772	0.065
Manufacturing (%)	−0.573^{FRH}	−2.230^{L}	−1.245^{H}	−1.880^{LH}	−3.972^{LAR}
Trade (%)	−5.767^{F}	−4.618^{LAR}	−5.683^{F}	−6.428^{F}	−6.335
Transportation, communication, utilities (%)	1.100^{AR}	0.982^{R}	0.546^{L}	0.049^{LF}	0.581
Finance, insurance, real estate (%)	0.675^{H}	0.932	0.676^{H}	0.847^{H}	1.837^{LAR}
Professional services (%)	−0.847^{FRH}	−0.194^{LA}	−0.755^{FRH}	−0.341^{LAH}	0.531^{LAR}
Education, health, social services (%)	5.745^{F}	7.003^{LA}	5.610^{F}	6.047	6.511
Leisure, business, other services (%)	7.874	7.187	7.971	7.735	6.840

Note: Scheffe's test indicates significant differences at $p < 0.05$ between low inequality (L), falling inequality (F), average inequality (A), rising inequality (R), and high inequality (H) clusters. Leisure industry includes arts, entertainment, recreation, accommodation, and food services.
Source: U.S. Census Bureau (1980 Census SF3 and 2005–09 American Communities Survey).

Discussion and Conclusions

This analysis fills an existing gap in the literature by specifically examining income inequality across subcounty places over time in non-metropolitan areas, and it complements existing work looking at poverty rates across the same geographic scales. The overall purpose is to identify and describe clusters of persistent low and high income inequality in rural block-groups in the western part of the NCR-W. The first key finding is that there are more low inequality places than high inequality places between 1979 and 2009. About one-fifth (21.5 percent) of block-groups are characterized as having persistently low income inequality, whereas only 3.4 percent of block-groups are considered as having persistently high inequality. This indicates that persistent inequality is currently not a major concern in the non-metropolitan NCR-W. However, the findings also indicate that there are more rising inequality places (26.9 percent) than falling ones (14.8 percent). This indicates that rising income inequality, not persistently high inequality, is the primary concern in the NCR-W. If current trends continue, over time these rising inequality places may become pockets of persistent inequality.

The second key finding is the presence of large numbers of high and rising inequality places in traditionally low poverty states, especially in Iowa, Minnesota, and Nebraska. Similarly there are large numbers of low and falling inequality places in typically high poverty states, like Missouri, North Dakota, and South Dakota. This suggests that high rates of poverty and high rates of inequality may operate in opposite directions, rather than in the same direction. Thus poor places can be highly equal in terms of income distributions, while prosperous places can be highly unequal. This is consistent with a body of research that finds a positive relationship between income inequality and economic growth (Bell and Freeman). According to this view, one would expect more prosperous places to have higher inequality than poorer places. However, Fallah and Partridge show that while this positive inequality–growth relationship holds at the national level and in metropolitan places in the Unites States, the reverse was found for rural places—contrary to what is found in this analysis. More research is clearly needed to better examine the inequality–growth relationship across geographic scales.

The third key finding is that lower inequality places have poorer demographic outcomes, as identified in the literature, than higher inequality places. Lower inequality places in the rural NCR-W tend to have more single-headed families, be more poorly educated, have lower participation in the economy, higher levels of poverty and near poverty, and have lower median incomes. By contrast, higher inequality places have fewer single-headed families, are better educated, have higher economic participation, lower levels of poverty and near poverty, and higher incomes. These correlates of poverty are well documented in the literature (Weber et al.), but the findings suggest that they may operate in different directions when used to examine income inequality. Thus the factors that may help to explain high rates of poverty may not help in explaining higher rates of inequality. Rather the results suggest that most correlates of high poverty help to explain lower rates of income inequality.

The fourth key finding is that lower inequality places are more specialized in traditional agricultural and industrial sectors, while higher inequality places are more specialized in higher skilled services industries. The results show that lower inequality places in the NCR-W have larger employment shares in agriculture, construction, and to some degree manufacturing; and smaller shares in higher skilled services employment. These places also had faster declines in agriculture, but tended to have smaller declines in manufacturing. By contrast, higher inequality places are specialized in financial, insurance, professional, business, education, and health services; and are less specialized in the agricultural and industrial sectors. These places experienced growth in higher skill services, slower declines in agriculture, and declines in manufacturing. These findings lend partial support to the social polarization thesis (Sassen), where the presence and growth of post-industrial services, and declines in goods-producing industries, leads to increasing levels of income inequality. However, the spatial distribution of inequality suggests that this is not occurring uniformly across the region, but only in certain pockets of the rural NCR-W.

In summary, the findings support the conclusion that successful economic growth and development in rural places are likely to result in increased income inequality at the local level. In fact, that this conclusion is drawn from data containing some of the lowest and slowest growing inequality places in the United States suggests that the inequality–growth relationship is not unique to more urban and more unequal places. Many state and federal programs appropriately direct their rural development efforts at (i) diversifying the employment base away from traditional sectors (such as agriculture and manufacturing) toward services industries; and (ii) stabilizing and growing populations in rural places. While such development efforts undoubtedly have a positive impact on reducing poverty and increasing general economic well-being, the unintended consequences of these efforts is increased inequality. Thus economic development efforts should also seek to enhance social and economic integration through reduced inequality. Such development programs should include strategies that help employ the least employable by removing common barriers, such as lack of child care, transportation, and mismatch of skills (Fallah and Partridge).

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