The Spatial Dynamics of Neighborhood Inequality in the 21st Century Metropolis

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Extended Abstract

In recent decades, a vast amount of literature has documented the deleterious effects of increasing geographic concentration of neighborhood poverty in U.S. metropolitan areas (Wilson 1987, 1996; Massey and Denton 1993; Jargowsky 1997). Specifically, extensive ethnographic work conducted by Wilson concluded that the pervasiveness of urban poverty concentration was due to factors such as an exodus of a black middle-class to the suburbs, a deteriorating inner-city employment sector, and the rise of female-headed families with children. Massey and colleagues stressed that high levels of racial residential segregation interacted with rising income inequality to exacerbate the already countless social, economic, and psychological ills and contribute to a growing urban underclass.

Researchers began to not only consider issues of concentrated poverty, but also investigate the importance of concentrated affluence in determining individual outcomes (Brooks-Gunn et al. 1993; Massey 1996). In order to account for statistical problems in measuring the proportion poor and the proportion affluent concurrently, Massey (2001) recommended measuring both effects along a continuum of concentrated poverty and concentrated affluence—the index of concentration at the extremes. Recently, many scholars have adopted the index as a measure of neighborhood inequality in predicting a wide range of outcomes, including crime and violence (Morenoff et al. 2001), employment and welfare use (Casciano and Massey 2007), and child development (Carpiano et al. 2009).

Although Massey and Eggers (1993) documented the spatial concentration of poverty using a class isolation index, to my knowledge there have been no studies assessing neighborhood inequality as the index of concentration at the extremes in multivariate models. In addition, social processes in urban areas, such as poverty, homicide, and collective efficacy are often localized at the neighborhood level, yet these processes are also determined by what happens in surrounding neighborhoods (Sampson et al. 1999; Morenoff et al. 2001; Voss et al. 2006). Thus, researchers run the risk of spatial autocorrelation and spatial dependence in the data structure (Anselin 1996). Spatial techniques can not only account for these potential issues, but also reveal diffusion processes of social behavior across artificial boundaries, such as census tracts.

The purpose of this study is to explore spatial patterns of neighborhood inequality in a large metropolitan area, Chicago, for 2000 and 2010. More importantly, I will investigate how changes in neighborhood inequality are influenced by changes in the structural characteristics of neighborhoods across space. I will accomplish these tasks by employing exploratory spatial analysis and spatial regression techniques. Results will demonstrate the extent to which two divergent outcomes—concentrated poverty and concentrated affluence—exhibit spatial patterning over time, and how these patterns are affected by changing structural processes.

Data and Methods

The data will be drawn from the U.S. Census Bureau SF3 for 2000 and the American Community Survey (ACS) estimates for 2005-2009. The neighborhood is the unit of analysis, which is defined as the census tract. There are 858 census tracts in Chicago. With the upcoming release of the ACS data, I will be able to assess change over the past decade, particularly the extent to which change in predictors are associated with changes in neighborhood inequality across time and space.

For my dependent variable, I use neighborhood inequality, which is termed the index of concentration at the extremes (ICE). Following the work of Massey (2001), I adopt the ICE as a measure of inequality that captures the concentration of both poverty and affluence. The calculation for a given neighborhood is as follows: (the number of affluent families – the number of poor families) / total number of families. Affluent families are defined as families with income above $75,000, and poor families are those families below the official poverty line. The ICE ranges from -1.0 to 1.0, where -1.0 indicates extreme poverty and 1.0 represents extreme affluence. An ICE of 0 indicates an equal share of affluent and poor families within a neighborhood. Given that this measure is constructed for arbitrarily-defined neighborhoods (census tracts), it is reasonable to anticipate a considerable amount of spatial autocorrelation and dependence in this variable, especially over time.

The explanatory variables for this analysis consist of a number of structural characteristics in Chicago neighborhoods. Several of these variables are highly correlated with each other and, therefore, may cause potential problems with multivariate model specification due to multicollinearity. Thus, based on previous work by Sampson and colleagues (1997), I perform a principal component analysis with oblique rotation, which results in the following three factors: 1) Concentrated Disadvantage: % African-Americans, % less than 18, % unemployed, % on public assistance, and % female-headed households with children; 2) Immigrant Concentration: % Latino and % foreign-born; and 3) Residential Stability: % homeownership and % same house in 1995. Additional multivariate models will include changes in the % married, % 18+ enrolled in school, % professional occupations, % new housing construction, and the racial heterogeneity of the neighborhood.

Exploratory Spatial Data Analysis (ESDA)

Quantile maps are used to visually depict the spatial distribution of the dependent variable, neighborhood inequality (ICE). Global Moran's I and Local Indicators of Spatial Autocorrelation (LISA) are employed to assess patterns of spatial autocorrelation. Global Moran's I indicates the prevalence of spatial clustering and is visualized by means of the Moran scatterplot (Anselin 1996), while LISA statistics indicate the location of these clusters, illustrated by significance maps. The scatterplot for the Local Moran generates four quadrants of local spatial autocorrelation: high-high; low-high; low-low; and high-low. For example, the high-high quadrant represents neighborhoods with high values of ICE that are surrounded by neighborhoods with similarly high values.

Spatial Regression

Spatial regression techniques will be employed to account for spatial dependence in the data and ultimately produce a parsimonious model with more reliable estimates. Spatial terms must explicitly be included in the regression equation and then re-run in order to arrive at consistent and unbiased estimators (Anselin 2000). Therefore, I will first run a standard OLS model and assess the diagnostics. Based on the diagnostics, I will then either estimate a spatial lag model or spatial error model. Spatial lag models imply feedback processes, such as adoption or diffusion, while the need for a spatial error model suggests autocorrelation in the error term or perhaps omitted variable bias.

Results

Preliminary results are presented for 2000 in order to demonstrate the justification and the need for spatial techniques when assessing the index of concentration the extremes (ICE) in Chicago. The distribution illustrated in Map 1 suggests considerable spatial patterns that depict high concentrations of poverty (dark red) on both the west and south sides, and high concentrations of affluence (light tan) on the north side and outer-city areas.

Figure 1 displays the scatterplot for the Global Moran's I statistics assessing neighborhood inequality. The results indicate strong and positive autocorrelation (.6908) in the ICE, which suggest that OLS estimates and standard errors may be potentially biased. These visual representations of the ESDA help in determining that neighborhood inequality in Chicago is spatially autocorrelated and the dependent on ICE levels in surrounding census tracts.

Table 1 presents the results from the OLS and spatial lag models of neighborhood inequality. For my OLS model, all three measures are highly significant and in the hypothesized direction. After examining the ESDA and the OLS diagnostics, I run a spatial lag model. Substantively, the spatial estimates are similar to those from the OLS specification, but the addition of a spatial lag term reduces the magnitude of neighborhood predictors. The fit statistics (log-likelihood, AIC, BIC) also indicate that the spatial lag model is an improvement over the OLS model.

These preliminary results provide support for the use of spatial techniques in assessing neighborhood inequality in Chicago. An analysis of neighborhood change in the early 21st century will shed light on the nature of concentrated affluence and concentrated poverty. Furthermore, this study will raise additional questions regarding the role of race and class in segregation processes and their relationships with a myriad of social and economic outcomes.

Map 1: Index of Concentration at the Extremes: Chicago Census Tracts, 2000

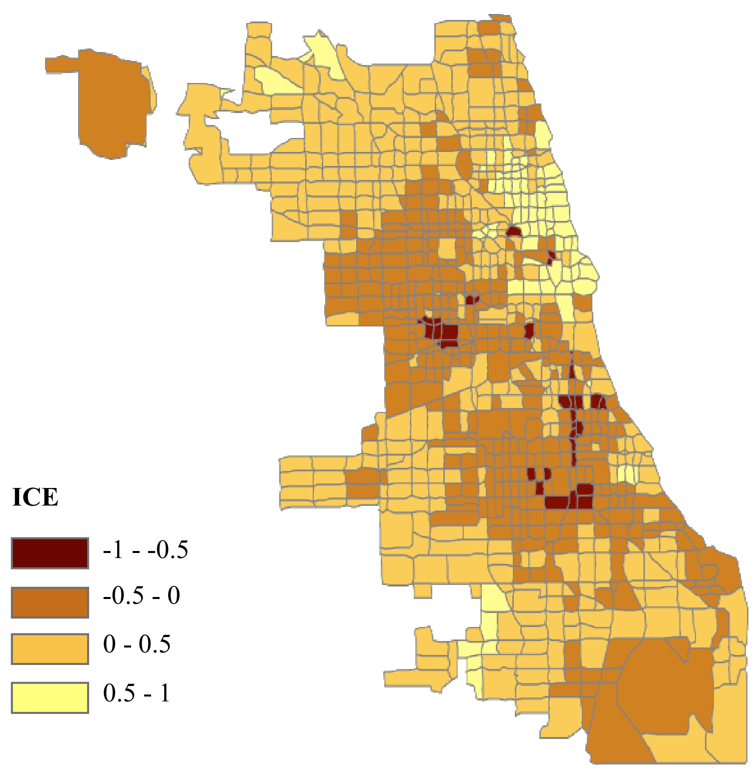

Figure 1: Moran's I Scatterplot of ICE: Chicago Census Tracts, 2000

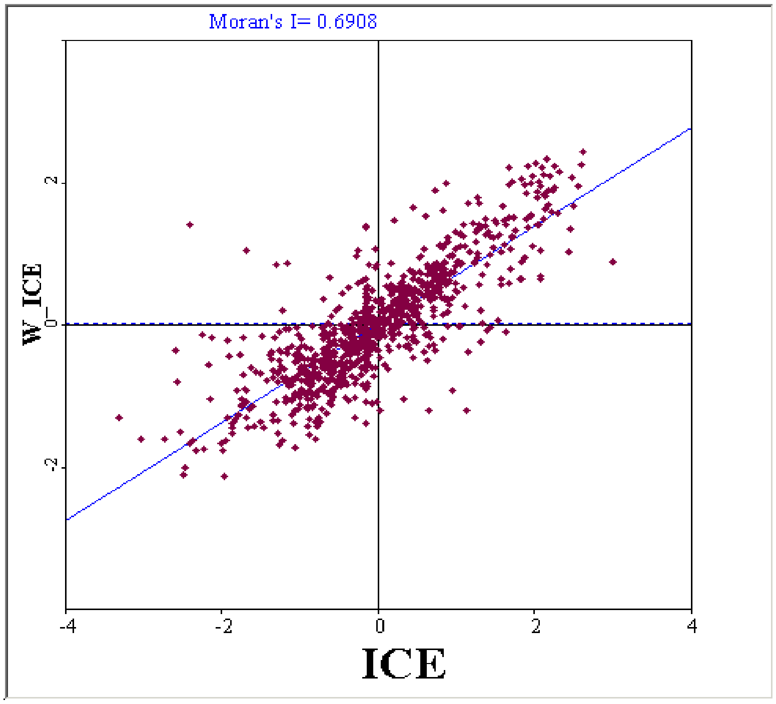

Table 1. OLS and Spatial Lag Models Predicting Index of Concentration at the Extremes, Chicago 2000

	OLS		Spatial Lag	
Independent Variables				
Disadvantaged Concentration	-.322	***	-.229	***
	(.006)		(.008)	
Immigrant Concentration	-.117	***	-.088	***
	(.007)		(.006)	
Residential Stability	.072	***	.063	***
	(.008)		(.007)	
Spatial Lag (ρ)	—		.386	***
			(.026)	
Intercept	.046	***	.028	***
	(.005)		(.005)	
Measures of Fit				
R^2	.757		.812	
Log Likelihood	376		471	
AIC	-745		-932	
BIC	-726		-909	
N	858			

Note: Standard errors in parentheses. Spatial weights matrix is rook first order.
*p < .05; **p < .01; ***p < .001.