Measuring trajectories of neighborhood poverty in California, 1970-2009

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Extended abstract

Background

Increasingly, health researchers are interested in understanding how spatial and residential contexts affect health. A growing body of research examines relations between health outcomes and neighborhood characteristics such as socioeconomic factors (e.g., concentrated poverty, neighborhood disadvantage), racial segregation, social context (e.g., social capital, social norms), and the built environment (Diez Roux & Mair, 2010). The vast majority of this literature uses cross-sectional measures of the neighborhood environment, yet neighborhood exposures measured at one point in time do not capture the dynamic natures of neighborhoods that could have important implications for health. The impacts on health of living in neighborhoods that have experienced long-term concentrated poverty, gentrification, or deterioration are unknown. Long-term concentrated poverty may, for example, be correlated with a lack of infrastructure, racial segregation, and high crime. Processes such as gentrification may lead to increased private and public investment, safety, and access to resources such as health care (Jargowsky, 2005; Kennedy & Leonard, 2001). However, rapid neighborhood change may also be a stressor for families struggling to cope with rising rents, and incoming residents may be younger and less invested in the social structure of the neighborhood (Nyden P., 2006).

To date, little research has attempted to measure these neighborhood social processes and to link them to health outcomes. One recent study found that an average measure of neighborhood poverty over a 16-year period was a stronger predictor of self-rated health than a single point measure, and that the association between the multipoint measure and health remained robust to adjustment for individual level risk factors (Do & Finch, 2008). Another study found that increasing census tract-level SES was associated with increased odds of breast cancer metastasis at diagnosis (Barrett et al., 2008).

Objective

The objective of this study is to compare methods for characterizing the long-term socioeconomic trajectories of neighborhoods in California. We first categorize neighborhoods based on percent poverty at one time point (2005-2009); we then use three methods to define trajectories of poverty from 1970-2009: 1) *a priori* definitions, 2) latent class growth modeling, and 3) non-parametric clustering. We then compare these categories to other neighborhood socioeconomic variables. Next steps will examine associations between neighborhood poverty trajectories and health outcomes.

Methods

<u>Data.</u> Data on neighborhood poverty rates was obtained from the Neighborhood Change Database (NCBD) and the American Community Survey 2005-2009 (ACS). The NCBD (published by Geolytics, Inc.) contains a comprehensive set of data on socioeconomic status, racial/ethnic composition, family structure, and housing characteristics from the 1970, 1980, 1990, and 2000 U.S. decennial censuses (Tatian, 2003). All data are normalized to Census 2000 boundaries so that comparisons are made on the same geographic boundaries over time (Tatian, 2003). The ACS is an ongoing annual survey that collects data similar to that of the US Census to provide more up-to-date information than the decennial census. The ACS provides 1- , 3-, and 5-year estimates; 5-year estimates have the largest sample size and are most reliable. We therefore use the 2005-2009 estimates for this study. Following prior work showing that census tracts are as effective as smaller administrative units in estimating associations between socioeconomic context and health outcomes (Krieger et al., 2003), we use census tracts as approximations of neighborhood in this study. We focus on census tracts in the state of California because of its size and diversity of communities in terms of racial/ethnic makeup, rural/urban and socioeconomic status, and economic base.

Variables. Our primary variable of interest was tract-level percent poverty, or the proportion of individuals in each census tract whose family income fell below the federal poverty level (FPL) in the last year. This variable is available from the NCBD for 1970, 1980, 1990, and 2000 and from the ACS for 2005-2009 (which we refer to as the most recent time point).

Other key socioeconomic variables included—at the census tract level—median housing value, percent crowded housing (percent of owner-occupied homes with >1.0 persons per room), percent of total population that was non-Hispanic white, percent of total population that was unemployed, and percent of adults over 25 years that had less than a high school education or at least a college education.

Classification of neighborhood poverty. We used four methods to categorize census tracts based on poverty. First, we categorized tracts based on percent poverty at the most recent time point. We classified tracts with <5% poverty as low poverty, those with 5-20% poverty as moderate poverty, and those with >20% poverty as high poverty. Next we used three methods to categorize tracts based on their poverty trajectories from 1970-2009.

A priori categorization of trajectories. We hypothesized that neighborhoods would fall into one of several poverty trajectories. First, many neighborhoods would have stable levels of poverty over time, i.e. stable low, stable moderate, or stable high. Second, some neighborhoods would "deteriorate" over time, or have increasing poverty. Third, some neighborhoods would gentrify over time, or have decreasing poverty. Of these deteriorating and gentrifying neighborhoods, we hypothesized that it would be important to understand whether these socioeconomic changes started relatively early (before 1990) or later (after 1990) in the study period. We categorized neighborhood poverty at each time point using the categories described above (low, moderate, and high). We then categorized neighborhood poverty trajectories as follows: stable low (all time points were either low or a combination or low and moderate with no discernible pattern), stable moderate (all time points were moderate), stable high (all time points were either high or a combination or high and moderate with no discernible pattern), early deterioration (tracts were low or moderate in 1970, became high or moderate by 1990, and remained high or moderate after that), late deterioration (tracts were low or moderate in 1970, became high or moderate by 2000, and remained high or moderate after that), early gentrification (tracts were high or moderate in 1970, became low or moderate by 1990, and remained low or moderate after that), and late gentrification (tracts were high or moderate in 1970, became low or moderate by 2000, and remained low or moderate after that).

Latent class growth modeling. Latent class growth modeling (LCGM), developed by Nagin and Land (Nagin & Land, 1993), identifies distinct subgroups of the sample that follow a similar pattern of change over time on a given variable (Andruff, Carraro, Thompson, Gaudreau, & Louvet, 2009), in this case, neighborhood poverty rates. Unlike the standard latent growth modeling, which estimates a single growth pattern for all and captures heterogeneity between units by random effects, LCGM enables estimation of heterogeneous growth patterns within a larger population. By fixing the variance and covariance estimates for the growth factors within each class to zero, all units within a trajectory are assumed to be homogeneous. The number of latent classes of neighborhood poverty was decided based on the Bayesian information criteria (BIC) value, the Lo, Mendell, and Rubin likelihood ratio test (LMR-LRT) statistic, and the entropy value. In general, a model with a smaller BIC value, a significant LMR-LRT statistic, and a higher entropy value indicates a better model. We estimated three distinctly different latent class growth models of poverty rates (stable low poverty, stable low/moderate poverty, and stable high poverty).

Trajectories estimated using clustering. The LCGM models have benefits with unbalanced data and/or high density of points; in this case, however, we have only 5 data points and perfect balance. The LCGM methods rely heavily on assumptions about the underlying structure of the data; moreover, the model is chosen based on fit criteria that are strongly influenced by sample size, making interpretation of results difficult if the latent model is true. In this context, simple nonparametric clustering is a compelling alternative, and thus we used a non-parametric clustering method known as hierarchical ordered partitioning and collapsing hybrid (HOPACH) based on partitioning around the mediod (PAM) to identify underlying clusters/trajectories (van der Laan & Pollard, 2003). This method iteratively combines partitioning and collapsing steps to create a hierarchical tree of clusters and a "mediod", or cluster center, which can be used to describe the characteristic pattern of the cluster. In addition, as with model-based clustering, the cluster pattern is chosen based on optimizing a criterion (mean split silhouette, or MSS) (van der Laan & Pollard, 2003); in this analysis, the distances that define the MSS were chosen to be simple Euclidean distances between units.

Bivariate analysis. We examined the associations between neighborhood poverty categories, using each of the four methods, and other tract-level sociodemographic variables: median housing value, percent crowded housing, percent non-Hispanic white, percent unemployed, percent without a high school education, and percent with at least a college education. We calculated the correlation between each set of two methods using a Spearman correlation coefficient.

Results

Of the 7,049 census tracts in California, 23% had a low poverty rate at the most recent time point, 55% had a moderate poverty rate, and 21% had a high poverty rate. Thirteen tracts were missing poverty data at the most recent time point. By defining poverty trajectories *a priori*, we found that 25% of tracts had stable low poverty, 22% had stable moderate poverty, 15% had stable high poverty, 16% experienced early deterioration, 9% experienced late deterioration, 6% experienced early gentrification, and 6% experienced late gentrification. The 13 tracts missing the most recent poverty estimate and 39 tracts that did not fall into any of the *a priori* trajectories were excluded from further analyses. Appendix A shows the actual poverty rate patterns in each category.

Using LCGM, we found that 65% of tracts had long-term low poverty, 26% had long-term low/moderate poverty, and 9% had long-term high poverty. The mean poverty rate among long-term low poverty neighborhoods was 6.5% and increased .3% per decade; among long-term low/moderate poverty neighborhoods, the mean was 14% with a 2% increase per decade, and in long-term high poverty neighborhoods, the mean was 28% and increased 3% per decade (Table 1). Figure 1 shows the poverty rates from 1970-2009 for all 7,049 tracts as well as the three latent class trajectories.

The HOPACH-PAM method identified eight clusters, illustrated in Figure 2. Each graph in Figure 2 depicts a random subset of tracts from that cluster as well as the mediod as a black stairstep. Neighborhoods in Cluster 1, which had low baseline poverty and experienced a slight decline in poverty over time, and neighborhoods in Cluster 2, which had stable low poverty over time, accounted for 15 and 20% of neighborhoods, respectively. Another set of neighborhoods with moderate baseline poverty experienced some decline in poverty over time and accounted for 19% of all neighborhoods (Cluster 3). The remaining 46% of neighborhoods fell into clusters that experienced deterioration (increasing poverty). About 8% of neighborhoods had low baseline poverty and experienced a substantial increase in poverty over time (Cluster 4), about 15% had moderate baseline poverty and experienced a slight increase over time (Cluster 5), about 8% had moderate baseline poverty and experienced a substantial increase in poverty (Cluster 6), about 10% had moderate/high baseline poverty and experienced a substantial increase in poverty (Cluster 7), and about 5% had high baseline poverty and experienced a substantial increase in poverty (Cluster 8). Findings from this method demonstrate that, although some neighborhoods did have stable or declining poverty over time from 1970-2009, almost half of all neighborhoods fell into clusters characterized by deterioration over time, and there was substantial variation in the baseline poverty as well as the pattern of change among these deteriorating clusters.

Table 2 demonstrates the correlation between categories identified using the four methods. The LCGM and HOPACH-PAM methods were highly correlated with each other ($\rho = 0.83$) and wit the most recent time point categories ($\rho = 0.66$ and 0.78, respectively). The *a priori* clusters were not highly correlated with the other methods.

Table 3 shows the distribution of other neighborhood-level socioeconomic variables by category for each of the four methods. Gradients in the expected direction can be seen across neighborhoods with low, moderate, and high poverty based on the most recent poverty rate. For example, median housing value decreases from $637,800 to $460,500 to $350,000 across these categories, while the percent of adults with less than a high school education increases from 8.2 to 18.5 to 39.2.

Socioeconomic and demographic characteristics of the theoretically defined categories show similar but more complex patterns. Gradients in the expected direction are also seen across the stable low, moderate, and high poverty categories. In addition, neighborhoods experiencing gentrification appear more similar to low poverty neighborhoods in terms of other socioeconomic and demographic variables, while neighborhoods experiencing deterioration appear more similar to high poverty neighborhoods. For example, the mean percent of non-Hispanic white in neighborhoods with early and late gentrification are 60.7 and 52.0, respectively, while in neighborhoods with early and late deterioration these means are 40.1 and 38.2, respectively. Although the early and late deterioration categories are somewhat similar, the impacts of deterioration at different time points are evident: neighborhoods with early deterioration have lower median housing value and percent of adults with at least a college education and higher percents crowded housing, non-Hispanic white, and adults with less than a high school education compared to neighborhoods with later deterioration. Similarly, early gentrifying neighborhoods have more favorable socioeconomic profiles and higher percents non-Hispanic whites compared to late gentrifying neighborhoods.

At first glance, the trajectories identified by the LCGM appear similar to the categories based on the most recent time point (low, moderate, and high). However, the socioeconomic profile of these trajectories suggests that looking at neighborhood poverty over time does not produce the same results as using data from only the most recent time point. Notably, neighborhoods with long-term high poverty are more disadvantaged than neighborhoods that have high poverty rates at the most recent time point.

The clusters identified by the HOPACH-PAM are also associated with other socioeconomic characteristics. These associations also confirm that, even within clusters with increasing rates of poverty overtime (e.g., Clusters 4-8), substantial variation in socioeconomic disadvantage exists. For example, although Cluster 4—which is characterized by low baseline poverty rate—experiences increasing poverty over time, it looks similar in terms of other socioeconomic characteristics to the stable low and moderate categories identified using the *a priori* method. On the other hand, Cluster 8, which is characterized by a high baseline poverty rate and increasing poverty to almost 40%, stands out as the most disadvantage category identified using any method. On the other hand, Cluster 1, which is characterized not only by low baseline poverty but by decreasing poverty over time, exhibits a remarkably favorable socioeconomic profile and high percents non-Hispanic white.

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Table 1. Intercepts and slopes for neighborhood poverty trajectories identified using latent class growth modeling, 1970-2009 (n=7,049 California census tracts)

	Estimates	S.E.	P value
Long-term low poverty			
Intercept	6.548	0.094	<.001
Slope	0.270	0.031	<.001
Long-term low/moderate poverty			
Intercept	13.955	0.373	<.001
Slope	2.017	0.084	<.001
Long-term high poverty			
Intercept	27.704	0.701	<.001
Slope	2.696	0.174	<.001

Figure 1. Poverty rates over time for all neighborhoods from 1970-2009 and trajectories from latent class growth modeling (n=7,049 California census tracts)

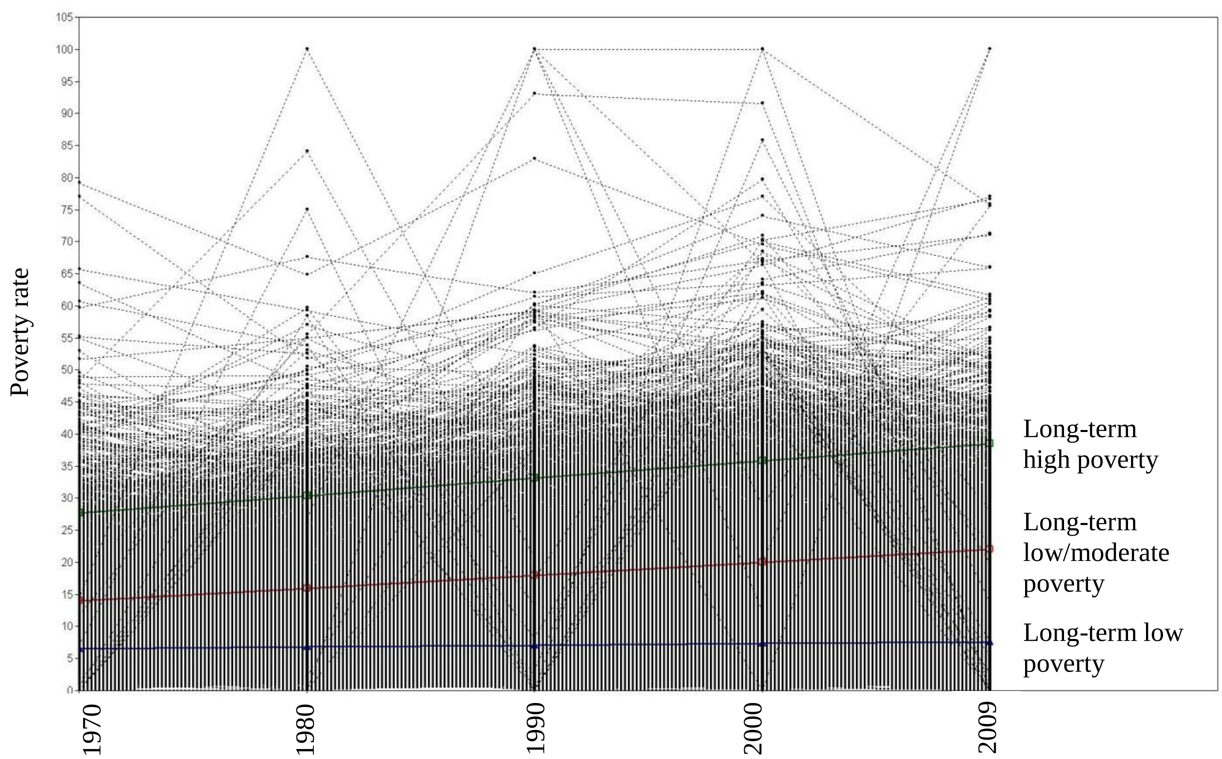
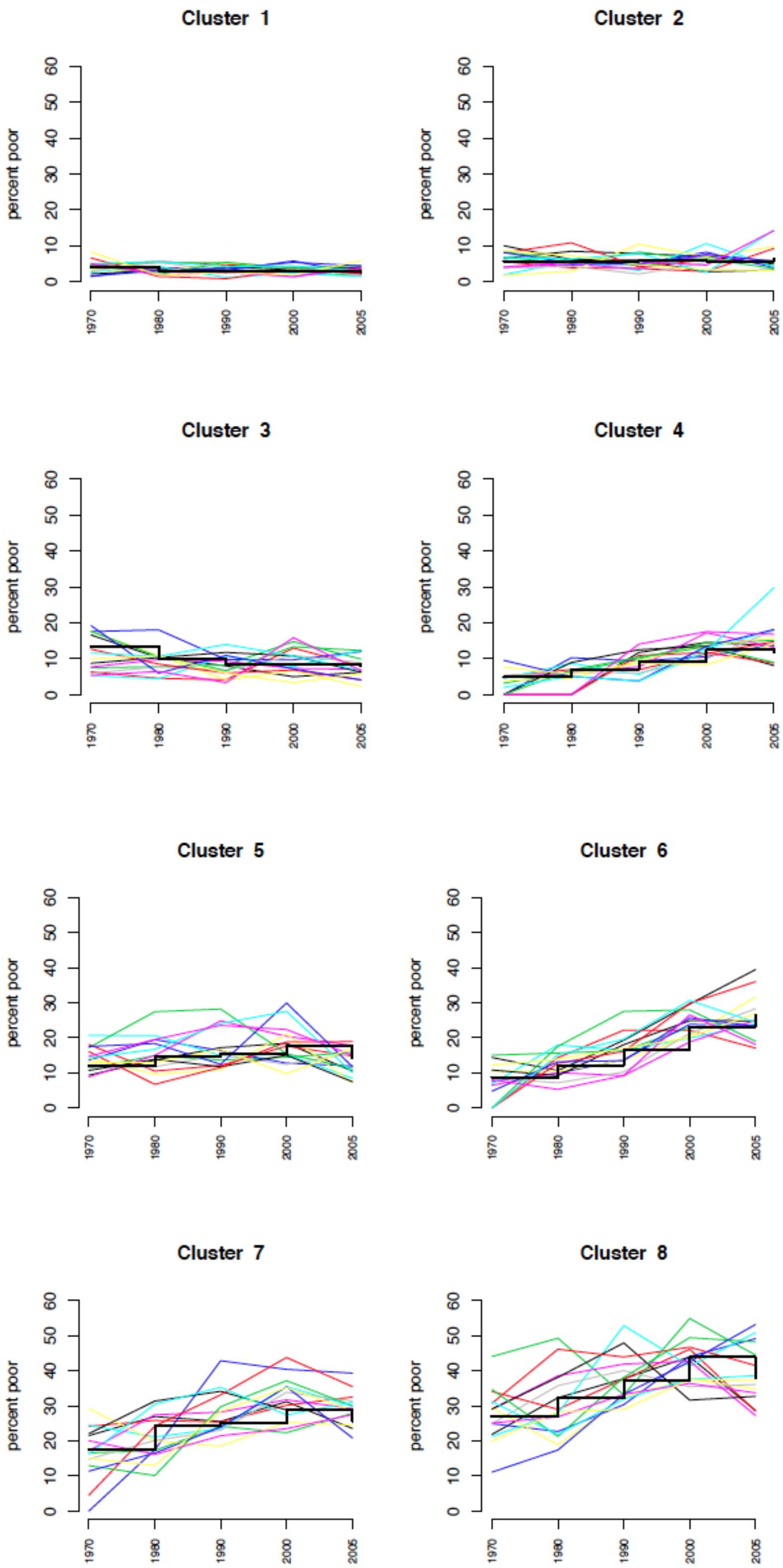


Figure 2. Results of HOPACH-PAM[1] clustering: poverty rates from 1970-2009 for a random subset of neighborhoods from each cluster and the mediod of that cluster, depicted as a black stairstep.



[1]Hierarchical ordered partitioning and collapsing hybrid (HOPACH) based on partitioning around the mediod (PAM)

Table 2. Spearman correlations between neighborhood poverty category methods

	2005-2009 poverty rate	*A priori* trajectories	Latent class growth curve modeling	HOPACH-PAM Clustering
2005-2009 poverty rate	1.00	0.26	0.66	0.78
A priori trajectories	0.26	1.00	0.32	0.38
Latent class growth curve modeling	0.66	0.32	1.00	0.83
HOPACH-PAM Clustering	0.78	0.38	0.83	1.00

Table 3. Distribution of census tract-level socioeconomic variables (2005-2009, American Communities Survey) by neighborhood poverty categories.

Neighborhood poverty categories	Number in category (% of total tracts)	Median housing value Median (SD)	Percent crowded housing[1] Mean (SD)	Percent non-Hispanic white Mean (SD)	Percent unemployed Mean (SD)	Percent of adults >25 years with less than a high school education Mean (SD)	Percent of adults >25 years with at least a college education Mean (SD)
2005-2009 poverty rate							
Low poverty (<5%)	1643 (23.4)	637,800 (213,545)	2.6 (4.5)	60.8 (0.2)	5.5 (0)	8.2 (0.1)	44.2 (0.2)
Moderate poverty (5-20%)	3885 (55.2)	460,500 (201,725)	7.6 (7.9)	45.6 (0.3)	7.8 (0)	18.5 (0.1)	28.8 (0.2)
High poverty (>20%)	1508 (21.4)	350,000 (160,646)	19.2 (12.4)	21.3 (0.2)	11.9 (0.1)	39.2 (0.2)	13.1 (0.1)
***A priori* trajectories (1970-2009)**							
Stable low poverty	1758 (25.0)	613,000 (208,811)	3.1 (4.2)	58.6 (0.2)	5.9 (0)	8.9 (0.1)	42.0 (0.2)
Stable moderate poverty	1579 (22.4)	451,850 (194,186)	8.0 (7.3)	43.5 (0.3)	7.8 (0)	19.6 (0.1)	27.5 (0.2)
Stable high poverty	1069 (15.2)	373,850 (162,712)	18.8 (11.8)	18.4 (0.2)	11.0 (0.1)	39.7 (0.2)	14.5 (0.1)
Early gentrification	432 (6.1)	604,900 (249,668)	2.6 (3.6)	60.7 (0.2)	6.3 (0)	9.2 (0.1)	41.5 (0.2)
Late gentrification	398 (5.7)	506,700 (216,961)	5.6 (7.7)	52.0 (0.3)	6.9 (0)	15.5 (0.1)	34.3 (0.2)
Early deterioration	1136 (16.2)	368,450 (178,756)	12.6 (12.4)	40.1 (0.3)	9.8 (0)	26.8 (0.2)	20.0 (0.1)
Late deterioration	625 (8.9)	424,300 (219,530)	10.3 (9.8)	38.2 (0.2)	9.4 (0.1)	22.5 (0.2)	25.8 (0.2)

Latent class growth curve modeling (1970-2009)							
Long-term low poverty	4602 (65.3)	541,150 (219,688)	4.5 (5.3)	54.7 (0.2)	6.7 (0)	12.5 (0.1)	36.0 (0.2)
Long-term low/moderate poverty	1845 (26.2)	371,800 (164,867)	15.2 (11)	27.3 (0.2)	10.3 (0.1)	32.4 (0.2)	17.3 (0.2)
Long-term high poverty	602 (8.5)	360,000 (168,456)	23.3 (12.9)	12.5 (0.2)	12.7 (0.1)	46.2 (0.2)	11.8 (0.2)
HOPACH-PAM Clustering (1970-2009)							
Cluster 1 (Low poverty, slightly decreasing)	1066 (15.2)	695,850 (193,648)	1.8 (3.7)	63.1 (0.2)	5.2 (0)	6.0 (0.1)	49.5 (0.2)
Cluster 2 (Stable low poverty)	1434 (20.4)	573,100 (199,797)	3.8 (3.8)	56.0 (0.2)	6.3 (0)	10.4 (0.1)	38.6 (0.2)
Cluster 3 (Moderate poverty, decreasing)	1346 (19.1)	465,100 (200,985)	5.6 (5.6)	50.1 (0.2)	7.3 (0)	15.4 (0.1)	30.5 (0.2)
Cluster 4 (Low poverty, increasing)	557 (7.9)	360,600 (158,261)	6.8 (5.9)	53.1 (0.3)	8.5 (0)	18.6 (0.1)	22.5 (0.1)
Cluster 5 (Moderate poverty, slightly increasing)	1022 (14.5)	409,850 (163,031)	12.2 (9.3)	31.5 (0.2)	9 (0)	27.9 (0.1)	20.2 (0.2)
Cluster 6 (Moderate poverty, increasing)	539 (7.7)	320,300 (147,049)	14.9 (10.3)	30.2 (0.2)	11.6 (0.1)	31.9 (0.1)	14.4 (0.1)
Cluster 7 (High/moderate poverty, increasing)	699 (9.9)	375,000 (164,931)	20.9 (12.6)	16.4 (0.2)	11.1 (0)	40.8 (0.2)	14.4 (0.2)
Cluster 8 (High poverty, increasing)	373 (5.3)	353,300 (163,171)	24.0 (13.0)	12.0 (0.2)	13.5 (0.1)	48.5 (0.2)	10.6 (0.1)

Appendix A. Patterns of neighborhood poverty status from 1970-2009 by category (from theoretically defined trajectories). Low poverty = <5%, moderate poverty = 5 to 20%, high poverty = >20%.

Category	**Number (% of category) with pattern**	**Pattern**				
		1970	**1980**	**1990**	**2000**	**2009**
Stable low	405 (23.0)	low	low	low	low	low
	96 (5.5)	low	low	low	mod	low
	41 (2.3)	low	low	mod	low	low
	34 (1.9)	low	low	mod	low	mod
	34 (1.9)	low	low	mod	mod	low
	86 (4.9)	low	mod	low	low	low
	50 (2.8)	low	mod	low	low	mod
	48 (2.7)	low	mod	low	mod	low
	76 (4.3)	low	mod	low	mod	mod
	22 (1.3)	low	mod	mod	low	low
	22 (1.3)	low	mod	mod	low	mod
	51 (2.9)	low	mod	mod	mod	low
	78 (4.4)	mod	low	low	low	mod
	62 (3.5)	mod	low	low	mod	low
	63 (3.6)	mod	low	low	mod	mod
	27 (1.5)	mod	low	mod	low	low
	23 (1.3)	mod	low	mod	low	mod
	32 (1.8)	mod	low	mod	mod	low
	83 (4.7)	mod	low	mod	mod	mod
	74 (4.2)	mod	mod	low	low	mod
	81 (4.6)	mod	mod	low	mod	low
	165 (9.4)	mod	mod	low	mod	mod
	105 (6.0)	mod	mod	mod	low	mod
Total	1758 (100.0)					
Stable moderate	**1579 (100.0)**	mod	mod	mod	mod	mod
Stable high	399 (37.3)	high	high	high	high	high
	195 (18.2)	mod	mod	mod	high	mod
	45 (4.2)	mod	mod	high	mod	mod
	24 (2.2)	mod	mod	high	mod	high
	85 (8.0)	mod	mod	high	high	mod
	20 (1.9)	mod	high	mod	mod	mod
	9 (0.8)	mod	high	mod	mod	high
	15 (1.4)	mod	high	mod	high	mod
	29 (2.7)	mod	high	mod	high	high
	16 (1.5)	mod	high	high	mod	mod
	11 (1.0)	mod	high	high	mod	high

	61 (5.7)	mod	high	high	high	mod
	10 (0.9)	high	mod	mod	mod	high
	13 (1.2)	high	mod	mod	high	mod
	17 (1.6)	high	mod	mod	high	high
	13 (1.2)	high	mod	high	mod	mod
	5 (0.5)	high	mod	high	mod	high
	14 (1.3)	high	mod	high	high	mod
	56 (5.2)	high	mod	high	high	high
	3 (0.3)	high	high	mod	mod	high
	6 (0.6)	high	high	mod	high	mod
	13 (1.2)	high	high	mod	high	high
	10 (0.9)	high	high	high	mod	high
Total	1069 (100.0)					
Early Gentrification	158 (36.6)	mod	low	low	low	low
	123 (28.5)	mod	mod	low	low	low
	1 (0.2)	mod	high	low	low	low
	1 (0.2)	mod	high	low	low	mod
	3 (0.7)	high	low	low	low	low
	4 (0.9)	high	low	low	mod	mod
	1 (0.2)	high	low	mod	mod	mod
	4 (0.9)	high	mod	low	low	low
	2 (0.5)	high	mod	low	low	mod
	3 (0.7)	high	mod	low	mod	low
	7 (1.6)	high	mod	low	mod	mod
	4 (0.9)	high	mod	mod	low	low
	9 (2.1)	high	mod	mod	low	mod
	8 (1.9)	high	mod	mod	mod	low
	89 (20.6)	high	mod	mod	mod	mod
	1 (0.2)	high	high	low	low	low
	1 (0.2)	high	high	low	mod	mod
	1 (0.2)	high	high	mod	low	mod
	2 (0.5)	high	high	mod	mod	low
	10 (2.3)	high	high	mod	mod	mod
Total	432 (100.0)					
Late Gentrification	99 (24.9)	mod	mod	mod	low	low
	204 (51.3)	mod	mod	mod	mod	low
	1 (0.3)	mod	mod	high	low	low
	2 (0.5)	mod	mod	high	mod	low
	3 (0.8)	mod	mod	high	high	low
	2 (0.5)	mod	high	high	mod	low
	2 (0.5)	mod	high	high	high	low
	1 (0.3)	high	mod	high	low	low
	1 (0.3)	high	mod	high	low	mod
	2 (0.5)	high	mod	high	mod	low

	2 (0.5)	high	high	high	low	low
	2 (0.5)	high	high	high	low	mod
	3 (0.8)	high	high	high	mod	low
	18 (4.5)	high	high	high	mod	mod
	2 (0.5)	high	high	high	high	low
	54 (13.6)	high	high	high	high	mod
Total	398 (100.0)					
Early Deterioration	182 (16)	low	low	mod	mod	mod
	10 (0.9)	low	low	mod	mod	high
	11 (1.0)	low	low	mod	high	mod
	9 (0.8)	low	low	mod	high	high
	1 (0.1)	low	low	high	mod	mod
	4 (0.4)	low	low	high	high	mod
	7 (0.6)	low	low	high	high	high
	348 (30.6)	low	mod	mod	mod	mod
	29 (2.6)	low	mod	mod	mod	high
	27 (2.4)	low	mod	mod	high	mod
	28 (2.5)	low	mod	mod	high	high
	8 (0.7)	low	mod	high	mod	mod
	3 (0.3)	low	mod	high	mod	high
	11 (1.0)	low	mod	high	high	mod
	28 (2.5)	low	mod	high	high	high
	9 (0.8)	low	high	mod	mod	mod
	1 (0.1)	low	high	mod	mod	high
	1 (0.1)	low	high	mod	high	high
	3 (0.3)	low	high	high	mod	mod
	1 (0.1)	low	high	high	mod	high
	3 (0.3)	low	high	high	high	mod
	36 (3.2)	low	high	high	high	high
	3 (0.3)	mod	low	high	high	high
	151 (13.3)	mod	mod	high	high	high
	222 (19.5)	mod	high	high	high	high
Total	1136 (100.0)					
Late Deterioration	123 (19.7)	low	low	low	low	mod
	1 (0.2)	low	low	low	low	high
	110 (17.6)	low	low	low	mod	mod
	1 (0.2)	low	low	low	mod	high
	2 (0.3)	low	low	low	high	mod
	1 (0.2)	low	mod	low	low	high
	4 (0.6)	low	mod	low	mod	high
	2 (0.3)	low	mod	mod	low	high
	1 (0.2)	mod	low	low	high	high
	1 (0.2)	mod	low	mod	low	high
	3 (0.5)	mod	low	mod	mod	high

	3 (0.5)	mod	low	mod	high	high
	3 (0.5)	mod	mod	low	mod	high
	1 (0.2)	mod	mod	mod	low	high
	164 (26.2)	mod	mod	mod	mod	high
	205 (32.8)	mod	mod	mod	high	high
Total	625 (100.0)					