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Journal

Crime & Delinquency, 68(11)

ISSN

0011-1287

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Publication Date

2022-10-01

DOI

10.1177/00111287211041527

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(Re)conceptualizing Neighborhood Ecology in Social Disorganization Theory: From a Variable- Centered Approach to a Neighborhood-Centered Approach

Crime & Delinquency
1–25

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DOI: 10.1177/00111287211041527

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Abstract

Shaw and McKay advanced social disorganization theory in the 1930s, kick-starting a large body of research on communities and crime. Studies emphasize individual impacts of poverty, residential instability, and racial/ethnic heterogeneity by examining their independent effects on crime, adopting a variable-centered approach. We use a “neighborhood-centered” approach that considers how structural forces combine into unique constellations that vary across communities, with consequences for crime. Examining neighborhoods in Southern California we: (1) identify neighborhood typologies based on levels of poverty, instability, and heterogeneity; (2) explore how these typologies fit within a disorganization framework and are spatially distributed across the region; and (3) examine how these typologies are differentially associated with crime. Results reveal nine neighborhood types with varying relationships to crime.

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Keywords

neighborhoods, crime, social disorganization, latent class analysis

In contrast to theories that advance “kinds of people” explanations for crime, social disorganization theory considers the effects of “kinds of places”—specifically, different types of neighborhoods—in creating conditions favorable or unfavorable to crime (Kubrin & Weitzer 2003, p. 374; Stark, 1987). Since Shaw and McKay first advanced the theory in the 1930s, a vast body of literature has produced important findings. There are, however, substantive and methodological deficiencies in this body of work (Bursik, 1988; Kubrin & Weitzer, 2003; Kubrin & Wo, 2016).

In the current study, we identify an additional deficiency, one that relates to how scholars conceptualize and operationalize the structural antecedents of social disorganization—that is, how they characterize neighborhoods and neighborhood structure. Studies emphasize the individual impacts of poverty, residential instability, racial/ethnic heterogeneity, and other structural characteristics by examining their unique, independent effects on neighborhood crime rates. In so doing, researchers take a variable-centered approach. Yet this approach has been critiqued, most notably by Abbott (1992) who identifies problematic assumptions of a variable-centered approach including that it is limited to the task of understanding the *relative* contributions that predictor variables make to a given outcome.

In light of these problematic assumptions, Abbott encourages researchers to “turn away” from the variables paradigm. We heed Abbott’s call and “turn away” from this paradigm to embrace a “neighborhood-centered” approach, consistent with some previous research (Warner, 2016, 2018; Warner & Settersten, 2017). This approach considers how neighborhood structural forces of interest in social disorganization theory combine into unique constellations or patterns that vary across communities, with consequences for crime. This approach intuitively maps onto the real-life experiences of neighborhoods and is more closely aligned with a holistic view of neighborhoods as “ecological niches” with varying distributions of risks and resources for residents (Warner & Settersten, 2017, p. 113). As such, the significance of any one aspect of neighborhood structure (e.g., poverty) gains meaning mostly in terms of its relations to other neighborhood characteristics (e.g., residential instability and racial/ethnic heterogeneity).

Combining data from several sources to examine neighborhoods in the Southern California region, we: (1) identify neighborhood typologies based on community levels of poverty, residential instability, and racial/ethnic heterogeneity; (2) explore how these neighborhood typologies fit within a social

disorganization framework and are spatially distributed across the region; and (3) examine how these typologies may be differentially associated with neighborhood crime rates. We compare findings from this approach to findings from the standard approach in the literature.

Below we review social disorganization theory as well as discuss findings from the literature. We then present a limitation with research and explain how a different approach to classifying neighborhoods more closely aligns with the theory's arguments. We next describe our data, methods, and findings. Finally, we conclude by discussing the implications of the findings and of this approach to classifying neighborhoods for social disorganization theory as well as for future neighborhood-crime studies.

Examining Social Disorganization Theory: From A Variable-Centered to A Neighborhood-Centered Approach

The original framing of social disorganization theory stressed that neighborhood disorganization emerges from a combination of disadvantageous conditions, most notably poverty, residential instability, and racial/ethnic heterogeneity (Shaw & McKay, 1969 [1942]). These attributes in relation to one another can lead to more or less disorganization within a neighborhood. For example, a neighborhood with high poverty and relative stability may be socially disorganized, but is likely less disorganized than a neighborhood featuring both high poverty and high instability. In the former, high poverty may limit cohesiveness and engagement within the neighborhood but the stability of residents may serve as a counterweight to social disorganization by increasing residents' sense of investment in their neighborhood. In the latter, however, residential instability may accentuate the effects of poverty. As originally theorized then, social disorganization—an organic condition within neighborhoods—reflects a constellation of factors which shape internal social dynamics; these constellations manifest in varying patterns.

Despite a theoretical emphasis on the interactive nature of the structural antecedents of social disorganization, researchers often adopt a non-interactive approach in their analyses. Measures are included for the structural characteristics that contribute to social disorganization and researchers observe their *ceteris paribus* associations with neighborhood crime rates, consistent with a variable-centered approach. While useful for addressing questions such as, what is the relationship between poverty and crime after controlling for racial/ethnic heterogeneity and residential instability?, it is unable to

determine just how structural characteristics operate simultaneously within communities.

Yet scholars have long identified multiplicative effects of the structural disorganization measures on crime. Bursik (1984) speculated that the influence of residential instability and population heterogeneity on crime rates varies with the economic status of areas because community organization is more essential to the fabric of life in poor communities. If community organization plays a greater role in the social control process of poor areas, then factors that weaken inter-personal networks, such as racial/ethnic heterogeneity and residential instability, should be more strongly associated with crime rates in lower- than in higher-status communities (see also Kubrin, 2000, p. 207). Unfortunately, few studies capture these multiplicative effects (Kubrin, 2000; Smith & Jarjoura, 1988; Warner & Pierce 1993; Warner & Rountree, 1997) and their findings typically do not support expected relationships. Studies testing the multiplicative relationship between racial/ethnic heterogeneity and residential instability, for example, fail to detect a significant interaction effect (Kubrin, 2000; Smith & Jarjoura, 1988; Warner & Pierce, 1993) while studies testing the possible interaction between poverty and racial/ethnic heterogeneity either fail to detect effects (Smith & Jarjoura, 1988) or find a negative relationship with crime (Warner & Pierce, 1993; Warner & Rountree, 1997). And while one study documents a positive relationship between the interaction of poverty and residential instability for violent victimization (Smith & Jarjoura, 1988), studies of neighborhoods in Boston (Warner & Pierce, 1993) and Seattle (Warner & Rountree, 1997) document a negative interaction effect.

There is need for additional work on how structural precursors to social disorganization operate in tandem to impact neighborhood crime rates. While studies examining interaction effects are a great start, another approach may be warranted. Before describing this approach, we identify limitations of a variable-centered approach.

Limitations of the Variable-Centered Approach

Variable-centered approaches describe associations between variables and are well-suited to the task of understanding the *relative* contributions that predictor variables make to a given outcome. Abbott (1992) has long critiqued this approach, arguing it rests on problematic assumptions including: (1) The social world is made up of fixed entities with varying attributes; (2) What happens to one case doesn't constrain what happens to others, temporally or spatially; (3) Attributes have one and only one causal meaning within a given study; and (4) Attributes determine each other principally as

independent scales rather than as constellations of attributes; main effects are more important than interactions. The implication, according to Abbott (1992), is that the method itself constrains theoretical thinking with a set of implicit assumptions, and these assumptions dictate how scholars imagine the social world to be constructed (p. 432).

There is certainly the ability to explore nonlinear effects in the variable-centered approach, although this is not frequently done and when it is, studies typically focus on a single variable at a time. Research has explored the possible nonlinear relationship between neighborhood poverty levels and crime, examining whether this is an exponential relationship or a slowing positive relationship (Hannon, 2005; Hannon & Knapp, 2003; Hipp & Yates, 2011; Krivo & Peterson, 1996). One study of census tracts in Columbus, Ohio concluded there was evidence of an exponential relationship between poverty and crime (Krivo & Peterson, 1996) whereas another study of block groups in Atlanta identified methodological limitations of earlier research and concluded that a linear relationship was actually observed (Hannon & Knapp, 2003). This issue was more exhaustively explored in a study of census tracts across 25 cities, which found that a slowing positive relationship was consistently observed (Hipp & Yates, 2011). Nonetheless, a limitation of all these studies is the narrow focus on the poverty and crime relationship, with no explicit consideration of how other measures may be simultaneously important.

Others agree a variable-centered approach does not capture possible heterogeneities in whatever the focus of study may be (Hill et al., 2000, p. 893). For this reason, the approach produces models that best describe the average behavior of the sample but that are least applicable to those cases showing the greatest deviations from the sample mean (Labouvie et al., 1991). Yet it is precisely these more extreme cases that may be most interesting to study in the first place.

A Different Approach and Expectations

Heeding Abbott's (1992) call, we adopt a different approach—one that examines how neighborhood structural forces in social disorganization theory combine into unique constellations or patterns that vary across communities, with consequences for crime. This strategy, introduced in some earlier work focused on various risk-taking behaviors by adolescents (Warner, 2016, 2018; Warner & Settersten, 2017), enables us to explore configurations of relevant neighborhood characteristics, more accurately capturing community context.

In the context of the current study, this approach intuitively maps on to the real-life experiences of neighborhoods, and is more closely aligned with a holistic view of neighborhoods as “ecological niches” with varying

distributions of risks and resources for residents (Warner & Settersten, 2017, p. 113). Thus, the significance of any one aspect of neighborhood structure (e.g., poverty) gains meaning mostly in terms of its relations to other neighborhood characteristics (e.g., residential instability and racial/ethnic heterogeneity). Consistent with prior work, we label this approach “neighborhood-centered” (Warner, 2016, p. 38, 2018; Warner and Settersten, 2017, p. 106).

What are the myriad ways that poverty, residential instability, and racial/ethnic heterogeneity interact with one another to generate unique neighborhood profiles? How do other neighborhood characteristics such as population density, the young male rate, and the foreign-born population distribute themselves across the different profiles? Which neighborhood profiles are associated with crime rates? Because this approach is uncommon in the literature, we adopt a more inductive approach and do not offer a priori specific hypotheses regarding expected results of the neighborhood typologies or of the relationships between the neighborhood types and crime rates (we save this discussion for the Conclusion Section of the paper). Yet findings from a handful of studies on the neighborhood context of drug use, sexual risk taking, and adolescent victimization (Warner, 2016, 2018; Warner & Settersten, 2017) inform our expectations.

Studying trajectories of adolescent/young adult marijuana use across neighborhood contexts, Warner (2016) adopts a similar approach to identifying neighborhood types. Her selection of neighborhood characteristics to consider is informed by several theories, including social disorganization theory, and thus she considers poverty, racial/ethnic composition, and urbanicity—among others—as salient factors that are likely to create diverse neighborhood contexts, each with potentially different effects on adolescent behavior. Using national data from Add Health, her findings reveal significant complexity in neighborhood context, with 10 neighborhood types identified based upon various combinations of these measures. Importantly, she finds that trajectories of marijuana use differ substantially across the neighborhood types, often in ways that seem counterintuitive. A key theme to emerge is that predominantly White neighborhoods are neither universally the most advantaged nor the most beneficial/protective against involvement in marijuana use, as some might predict.

The focus in the current study is not national but spans the Southern California region. Still, we have no reason to believe that the neighborhood profiles generated in our analysis will look significantly different than those identified in Warner (2016), especially when it comes to the number of meaningful contexts identified. For this reason, we expect our analysis to produce around 10 classes of neighborhoods, consistent with Warner. Likewise, given

Southern California's racial and ethnic diversity, we expect several classes to differentiate along race/ethnicity *and* class lines, where we expect to find homogeneous (in this context, largely white or Latino) poor and middle-class neighborhoods as well as racially/ethnically heterogeneous poor and middle-class neighborhoods, also consistent with Warner (2016). At the same time, unlike Warner, we also consider the role of neighborhood residential instability, which is likely to intersect in interesting ways with poverty and racial/ethnic heterogeneity, so we expect several neighborhood classes to diverge from her results. While it is difficult to predict the exact number of neighborhood profiles that will emerge as well as identify how the structural sources of social disorganization will distribute themselves across the Southern California landscape, we are confident that our analysis will produce a wide variety of "ecological niches" that go beyond traditionally organized and disorganized communities.

Before describing our data and methods and reporting the findings, it is critical to acknowledge the version of social disorganization theory that we review above and examine in the study's main analyses reflects the theory's original framing. We recognize this approach necessarily ignores important theoretical developments, most notably the increasing focus on "concentrated disadvantage" and other structural characteristics of communities that matter for crime. However, our decision to take this approach is intentional. The choice to emphasize the theory's original framing and to include individual measures rather than combined indices is influenced both by our desire to adhere as closely as possible to the fundamental tenets of the theory and to create neighborhood profiles that are more easily interpretable. This desire stems from our position that—far from being a final statement—this study is a starting point for investigating how neighborhood structural forces of interest in social disorganization theory combine into unique constellations that vary across communities, with consequences for crime. Nonetheless, in an attempt to apply the neighborhood-centered approach to a more contemporary version of the theory, as we discuss below, we conducted ancillary analyses that include key structural measures typically combined into indices to reflect "concentrated disadvantage" and "residential instability," and demonstrate additional insights that this neighborhood-centered approach can yield.

Data and Methods

Our study context is the Southern California region, which includes three metropolitan statistical areas: Los Angeles-Long Beach-Santa Ana, the second largest metro area in the U.S. (12.8 million population); Riverside-San

Bernardino-Ontario, the 12th largest (4.2 million population); and San Diego-Carlsbad-San Marcos, the 17th largest (3.1 million population). We examine tracts in five counties: Los Angeles, Orange, Riverside, San Bernardino, and San Diego. Our study features two stages of analysis. First, we conduct latent class analysis (LCA) on three structural measures derived from social disorganization theory—percent living in poverty, racial/ethnic heterogeneity, and average length of residence—for all 4,532 tracts in the region with at least 300 population.¹ After identifying the neighborhood classes, we descriptively analyze each to determine how they fit within the social disorganization framework and we examine their demographic and spatial profiles. For the second stage of analysis, we include the neighborhood classes in a series of negative binomial regression models to assess their relationships with crime rates for tracts in cities with crime data.

Dependent Variables

Our dependent variables reflect neighborhood-level counts of violent and property crime. The crime data were collected by directly contacting police departments across the region as part of the Southern California Crime Study (SCCS).² After geocoding crime incident addresses using ArcGIS v10.2 and aggregating the data to census tracts, our unit of analysis,³ we computed 3-year average counts of violent (aggravated assault, murder, robbery)⁴ and property (burglary, larceny, motor vehicle theft) crime, respectively, for the years 2009 to 2011, making 2010 the midpoint of our analyses. Computing 3-year crime averages smooths over any year-to-year variability.

Independent Variables

We computed independent variables using American Community Survey (ACS) data averaged over 5 years from 2006 to 2010. First, we constructed the social disorganization structural measures: *Percent living in poverty* reflects the percentage of individuals living in poverty; Racial and ethnic mixing is measured using a Herfindahl index of *racial/ethnic heterogeneity* based on five groups (white, African American, Latino, Asian, other race); and *residential instability* is computed as average length of residence, in years, multiplied by -1 such that each one-unit increase corresponds with one fewer year of residence, on average (i.e., instability).

We included additional variables in our models given their relationship to crime and to minimize the possibility of obtaining spurious relationships. Given evidence that neighborhoods with more immigrants have lower crime rates (Ousey & Kubrin, 2018), we created a measure of the *percentage*

foreign-born residents. To account for those in prime crime offending ages (Bellair, 1997), we created a measure of *percentage of residents aged 16 to 29*. We created a measure of neighborhood *population density* defined as population per square mile, given that high density neighborhoods can have higher crime rates (Boessen & Hipp, 2015). As land use characteristics can offer criminal opportunities (Brantingham & Brantingham, 1984), we constructed four measures capturing land use characteristics. We computed the proportion of area in the tract devoted to: (1) *industrial*, (2) *office*, (3) *residential*, and (4) *retail* purposes (reference category is any other land use designations). Finally, we accounted for possible spatial effects by creating spatially lagged versions of the socio-demographic control variables. Spatial lag variables were computed with an inverse distance decay capped at five-miles.

Methods

There are two stages of analysis. In the first stage, we used a clustering routine to combine the focal measures of interest—poverty, residential instability, and racial/ethnic heterogeneity—into latent clusters. We used a latent class analysis (LCA) strategy given desirable properties of the approach (Warner, 2016, p. 41). LCA groups together observations that are most similar on the variables in the analysis and allows the groups to be of varying sizes. One attractive feature is that whereas a challenge with all clustering strategies is the selection of the number of classes as the optimal model, the LCA provides a log likelihood solution that can be used to compute Bayesian Information Criterion (BIC) values, and researchers can select the optimal model with the lowest BIC value. The BIC provides a penalty for additional parameters. Second, a challenge with clustering algorithms is the inherent arbitrariness in strategies that begin by randomly selecting seed cases to begin the clusters (Steinley, 2003). The LCA approach does not require the selection of “initial cases,” avoiding this problem. Finally, there is the challenge of possibly obtaining a locally optimal solution rather than a globally optimal one (Hipp & Bauer, 2006) but this can be obviated by estimating the model multiple times with various random start values, an approach that is now automated in software (Muthén & Muthén, 1998–2007). Finally, the LCA approach is conceptually appealing, as it empirically determines *latent classes* that have similarity based on measures of interest. Thus, it assumes there is something about a group of neighborhoods that yields a particular constellation of values on the measures of interest, which maps onto our theoretical approach. The model estimates the probability that a given tract belongs to each of the classes. After estimating the model, we assign each neighborhood to the latent class for which it has the highest probability.

We estimated the LCA models in MPlus v5.21. The models include all census tracts in the Southern California region with a population of at least 300 residents ($N=4,532$). For each model, we specified 1000 random start values for the model parameters with 10 iterations each; then, we took the 500 models with the greatest maximum likelihood values and estimated them completely (Hipp & Bauer, 2006). To identify empirically the optimal number of neighborhood classes for our data, we estimated a series of LCA models with sequentially greater numbers of specified classes (e.g., three class solution, four class, five class, etc.) and compared model BIC values, as well as the substantive characteristics of the solution. Comparing across models, a nine-class solution provided the optimal fit for our data as it had a low BIC value and a high entropy value (implying the model is relatively good at placing each tract into a particular latent class; average probability per tract was .707).⁵ Thus, across the region, we identified nine distinct types of neighborhoods based on social disorganization measures.

In the second stage of analysis, we estimate negative binomial regression models in which the outcome variable is the count of property crime or violent crime. We include the latent classes as covariates in these models, as we are interested in the extent to which membership in these various classes explains levels of crime. These models include the control variables as well as logged population as an exposure variable (effectively transforming our outcome variables into rates). We estimate another set of models where we include the three social disorganization structural measures as separate variables, consistent with the traditional approach in the literature allowing us to compare findings from the two strategies. We find no evidence of multicollinearity in the models, as all variance inflation factors for our latent classes were below 3. There is also little evidence of spatial collinearity, as the Moran's I values for the estimated residuals were .07 for violent crime and .026 for property crime. Although our broad sample of census tracts across the region provides generalizability for the findings, we also estimated ancillary models including city fixed effects. This strategy assumes that only differences *within* city are meaningful.⁶ Despite the loss in statistical power, the results were broadly similar to those presented in our analyses, providing additional confidence in our results.

Results

Analysis 1: Descriptions of the Nine Classes

As shown in Figure 1, the nine neighborhood classes exhibited varied patterns across the social disorganization spectrum. For ease of interpretation,

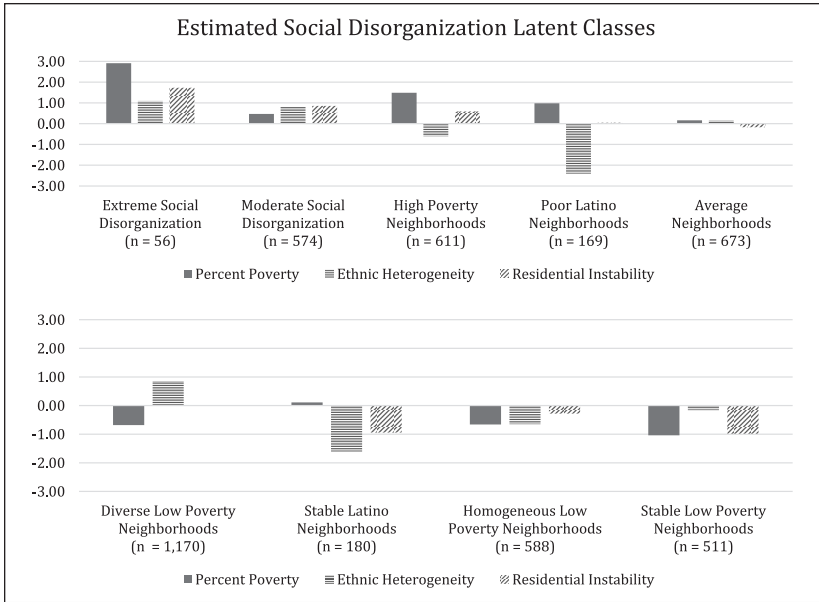


Figure 1. Estimated neighborhood classes based on social disorganization measures.

Note. Y-axis presented in standard deviation units.

we present standardized z-scores in this figure.⁷ As such, a value of zero represents the average value across all census tracts in Southern California (i.e., grand mean) whereas positive values indicate values higher than the grand mean and negative values indicate values lower than the grand mean. Positive values on any of the structural variables reflect neighborhood conditions consistent with social disorganization.

A richer description of the classes is provided in Table 1, which presents socio-demographic statistics for each class sub-sample and, for comparative purposes, the overall region. In this table we also present standardized z-scores to give a relative sense of each measure. Figure 2, which accompanies Table 1, maps the spatial clustering of three classes: *Poor Latino*, *High Poverty*, and *Diverse Low Poverty*.

Across the nine neighborhood classes, the *Average Neighborhoods* class ($n=673$) represents the quintessentially average neighborhood based upon social disorganization levels. Measures of poverty, heterogeneity, and instability are all approximately equal to the grand means for Southern California. Indeed, the neighborhoods in this class are average across all of

Table 1. Descriptive statistics for socio-demographic variables based on nine latent classes.

Independent variables	Full Sample		Extreme social disorg.		Moderate social disorg.		High poverty		Poor Latino		Average		Diverse low poverty		Stable Latino		Homog. low poverty		Stable low poverty	
	N = 4,532	N = 56	N = 574	N = 611	N = 169	N = 673	N = 1,170	N = 180	N = 588	N = 511										
Social disorganization measures																				
Pct. poverty	14.17	44.13 [2.69]	19.83 [0.51]	30.99 [1.51]	25.52 [1.02]	16.14 [0.18]	6.76 [-0.67]	15.54 [0.12]	7.01 [-0.64]	2.70 [-1.03]										
Ethnic heterogeneity	47.87	66.17 [1.07]	61.55 [0.80]	36.96 [-0.64]	5.94 [-2.46]	50.41 [0.15]	62.44 [0.85]	19.68 [-1.65]	36.67 [-0.66]	43.53 [-0.25]										
Residential instability	-9.91	-3.75 [1.71]	-6.83 [0.85]	-7.81 [0.58]	-9.81 [0.03]	-10.55 [-0.18]	-9.90 [0.00]	-13.40 [-0.97]	-10.87 [-0.27]	-13.37 [-0.96]										
Racial/ethnic composition																				
Pct. Asian	11.76	20.15 [0.60]	13.71 [0.14]	6.84 [-0.35]	1.21 [-0.76]	10.97 [-0.06]	18.23 [0.47]	3.37 [-0.60]	7.40 [-0.31]	12.23 [0.03]										
Pct. Black	6.38	13.85 [0.69]	9.69 [0.30]	9.15 [0.25]	0.58 [-0.53]	8.39 [0.18]	6.11 [-0.02]	4.55 [-0.17]	3.55 [-0.26]	2.31 [-0.37]										
Pct. Latino	41.91	29.05 [-0.46]	42.21 [0.01]	69.10 [0.98]	94.65 [1.89]	45.93 [0.14]	32.22 [-0.35]	72.61 [1.10]	25.13 [-0.60]	18.37 [-0.84]										
Pct. White	37.49	33.03 [-0.16]	31.56 [-0.21]	13.50 [-0.86]	3.25 [-1.23]	32.53 [-0.18]	40.06 [0.09]	18.51 [-0.68]	61.50 [0.86]	64.33 [0.97]										
Pct. Foreign-born	31.01	29.80 [-0.08]	34.35 [0.22]	43.18 [0.81]	48.59 [1.17]	32.35 [0.09]	28.45 [-0.17]	36.23 [0.35]	21.49 [-0.63]	20.22 [-0.72]										
Population/households																				
Pct. aged 16-29	18.01	38.00 [2.47]	21.24 [0.40]	20.94 [0.36]	20.28 [0.28]	18.79 [0.10]	17.40 [-0.08]	18.40 [0.05]	14.32 [-0.46]	12.42 [-0.69]										
Pct. aged 65 +	11.29	7.15 [-0.53]	9.25 [-0.26]	7.56 [-0.48]	7.07 [-0.55]	11.23 [-0.01]	10.69 [-0.08]	11.42 [0.02]	16.69 [0.70]	15.07 [0.49]										
Pct. families with children	49.38	49.52 [0.01]	52.10 [0.21]	59.55 [0.79]	59.85 [0.81]	48.08 [-0.10]	48.59 [-0.06]	49.62 [0.02]	41.11 [-0.64]	43.63 [-0.45]										
Pct. bachelor's degree	27.66	34.19 [0.34]	23.86 [-0.20]	11.12 [-0.85]	5.22 [-1.16]	21.88 [-0.30]	32.56 [0.25]	13.35 [-0.74]	39.72 [0.62]	45.96 [0.95]										
Median income	29,861	16,834 [-0.99]	24,025 [-0.44]	17,705 [-0.92]	17,708 [-0.92]	25,206 [-0.35]	34,166 [0.33]	23,605 [-0.47]	38,071 [0.62]	45,426 [1.18]										
Pop. density (per 1,000)	9.62	16.76 [0.76]	13.24 [0.38]	17.28 [0.81]	19.56 [1.05]	8.96 [-0.07]	6.71 [-0.31]	9.16 [-0.05]	5.69 [-0.42]	4.55 [-0.54]										

Note. Means are displayed, with z-scores in brackets below.

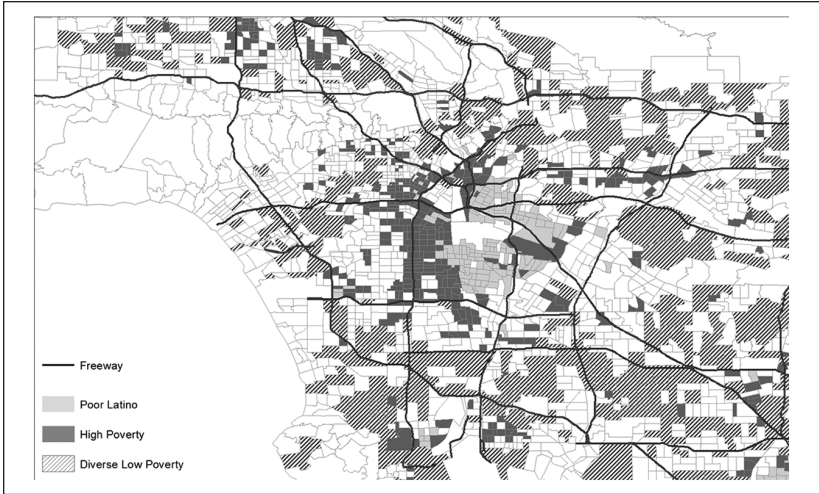


Figure 2. Diverse low poverty, high poverty, and poor Latino neighborhood classes in Los Angeles County.

the demographic characteristics, and these neighborhoods are more or less randomly distributed across the region, appearing in each of the counties. Its overall profile suggests that the *Average Neighborhoods* class embodies a natural reference class for comparisons with other neighborhood classes.

The configuration of the *Extreme Social Disorganization* class ($n=56$) reflects the standard theoretical model of a socially disorganized neighborhood, displaying high levels of poverty, racial/ethnic heterogeneity, and residential instability. The average racial/ethnic composition in these neighborhoods is 20% Asian, 14% black, 29% Latino, and 33% white, indicating substantial racial/ethnic mixing. Moreover, residents in these neighborhoods earned the lowest median income across the classes and lived in high population density. Across the region, *Extreme Social Disorganization* neighborhoods appeared spatially diffuse but demonstrated small pockets of clustering in cities such as Los Angeles.

Neighborhoods in the *Moderate Social Disorganization* class ($n=574$) demonstrate similarities with those identified in the *Extreme Social Disorganization* class exhibiting greater than average levels of poverty, racial/ethnic heterogeneity, and residential instability (although the magnitude of these measures is weaker than in the *Extreme Social Disorganization* class). Residents in these neighborhoods earn lower than average incomes and live in highly dense areas. *Moderate Social Disorganization* neighborhoods are

spatially diffuse and occupy relatively small pockets of clustering across the region. This class also demonstrates differences with its more extreme counterpart, featuring, on average, a notably larger Latino population (42%) and a smaller Asian population (14%). Median income is below the regional average but is \$7,000 higher than in *Extreme Social Disorganization* neighborhoods.

The *Poor Latino Neighborhoods* ($n=169$) and *High Poverty Neighborhoods* ($n=611$) classes exhibit similarities in their profiles. Both are characterized by elevated poverty levels. The *High Poverty Neighborhoods* not only have very high poverty rates but have higher than average levels of residential instability. Yet both classes diverge from the classic disorganization model by exhibiting greater than average levels of racial/ethnic *homogeneity*. Latino residents are especially prevalent, on average, in *Poor Latino Neighborhoods* (95%) and *High Poverty Neighborhoods* (69%). These neighborhoods also feature the highest percentages of foreign-born residents across the classes (49% in the *Poor Latino Neighborhoods* class), and are characterized by higher percentages of households with children (60% for both classes), lower than average incomes, and high population density (density in *Poor Latino Neighborhoods* is the highest of all of the classes). Finally, both classes demonstrate spatial clustering within and around the city of Los Angeles, although *High Poverty Neighborhoods* show clustering in other cities as well.

Similar to the *Poor Latino* and *High Poverty Neighborhoods* classes, the *Stable Latino Neighborhoods* class ($n=180$) features large Latino populations—73% of residents, on average—although this class exhibits a unique profile along the disorganization measures, and is characterized by higher than average levels of racial/ethnic homogeneity and residential stability and features average levels of poverty. *Stable Latino* neighborhoods have relatively low values on the structural determinants of social disorganization compared to the *Poor Latino* and *High Poverty* neighborhoods. Neighborhoods in the *Stable Latino* class demonstrated some spatial clustering within the city of Los Angeles, although they are also dispersed across the region.

The *Stable Low Poverty* ($n=511$) and *Homogeneous Low Poverty* ($n=588$) classes also reflect neighborhoods that have relatively low values on the structural determinants of social disorganization. Namely, these classes feature neighborhoods with lower than average levels of poverty and instability and average or higher levels of racial homogeneity (as the names imply, one is very high on residential stability whereas the other is very high on racial/ethnic homogeneity). Both sets of neighborhoods are predominately white and feature comparatively large elderly populations. These neighborhoods also exhibit the highest median incomes across the classes, the highest percentages of residents with at least a bachelor's degree, and are located in

areas with the lowest population densities. Both classes are dispersed across Southern California, particularly in Los Angeles County, Orange County, and San Diego County.

Finally, the *Diverse Low Poverty* ($n=1,170$) neighborhoods reflect a distinct profile that differs from the other classes. *Diverse Low Poverty* neighborhoods are characterized by lower than average poverty rates yet *higher* than average levels of racial/ethnic heterogeneity (but average levels of instability). Neighborhoods within this class, on average, are predominately white (40%) and Latino (32%), and residents have higher than average rates of bachelor's degree attainment and median income levels, and live in areas with lower than average population densities. This class contains the most neighborhoods in its sub-sample compared to the other classes.

Analysis 2: Regression Models Predicting Violent and Property Crime

To answer the research question—do these latent classes help explain the spatial distribution of crime in neighborhoods?—we turn to results from the negative binomial regression models. First, we consider violent crime. The first model in Table 2 includes dummy indicators for the neighborhood class assigned to each tract in the sample (*Average Neighborhoods* is the reference category) along with control variables. Model 1 shows that violent crime is 65% higher in *Extreme Social Disorganization* tracts compared to *Average Neighborhoods* tracts ($\exp(.498)-1 = .65$), consistent with social disorganization theory. We also see that compared to *Average Neighborhoods* tracts, *High Poverty* tracts have 28% more violence and *Poor Latino* tracts have 34% more violence, whereas rates of violence are 23% lower in *Diverse Low Poverty* tracts, 27% lower in *Homogeneous Low Poverty* tracts, and 45% lower in *Stable Low Poverty* tracts. Notably, *Moderate Social Disorganization* tracts do not have more crime than do *Average Neighborhood* tracts, suggesting there is not a linear effect of the disorganization measures but rather an impact in extreme cases.

In model 2, we include the three measures capturing the structural characteristics of social disorganization as separate variables, along with the controls, consistent with a variable-centered approach. The variance explained in this model is similar to model 1, so at first glance there appears to be little difference between the models. Yet comparing the two, we see that the neighborhood approach offers more nuanced results. In model 2, we observe that racial/ethnic heterogeneity, independent of other structural measures, is not significantly related to violence. Yet racial/ethnic heterogeneity comprises a critical role in many neighborhood profiles that are

Table 2. Negative Binomial Regression Models Predicting Violent and Property Crime.

	Violent crime models		Property crime models	
	(1)	(2)	(3)	(4)
C7: Extremely socially disorganized	0.498** (3.76)		0.236* (2.19)	
C8: Moderately socially disorganized	-0.022 - (0.39)		0.081 [†] (1.80)	
C3: High poverty	0.244** (4.23)		0.004 (0.08)	
C1: Poor Latino	0.295** (3.19)		-0.029 - (0.39)	
C9: Diverse low poverty	-0.257** - (5.23)		-0.094* - (2.45)	
C5: Stable Latino	0.140 [†] (1.66)		-0.127 [†] - (1.90)	
C6: Homogeneous low poverty	-0.309** - (5.33)		0.003 (0.06)	
C4: Stable low poverty	-0.607** - (9.64)		-0.148** - (3.07)	
Socio-demographic variables				
Racial/ethnic heterogeneity		0.000 - (0.29)		0.000 (0.00)
Percent in poverty		0.038** (21.69)		0.010** (7.40)
Residential instability		-0.020** - (4.12)		0.021** (5.54)
Percent aged 16-29	0.009** (3.47)	0.010** (3.61)	0.004* (2.03)	0.000 (0.20)
Percent immigrants	0.005** (2.65)	0.004* (2.32)	-0.003 [†] - (1.71)	-0.005** - (3.43)
Population density	-0.012** - (4.52)	-0.015** - (5.65)	-0.031** - (16.97)	-0.035** - (18.75)
Percent industrial land	0.684** (4.19)	0.726** (4.52)	0.817** (6.51)	0.880** (7.04)
Percent offices	-1.481** - (5.30)	-1.269** - (4.61)	1.486** (6.55)	1.448** (6.46)
Percent residential land	-0.230** - (3.14)	-0.179* - (2.49)	0.220** (3.94)	0.319** (5.64)
Percent retail land	3.111** (12.81)	3.112** (13.01)	3.611** (19.36)	3.515** (18.97)
Spatial lag of immigrants	-0.023** - (7.54)	-0.021** - (6.64)	-0.011** - (4.63)	-0.007** - (2.74)
Spatial lag of aged 16-29	0.039** (6.13)	0.031** (4.91)	0.037** (8.29)	0.034** (7.67)
Spatial lag of population density	0.050** (10.14)	0.044** (9.25)	0.031** (8.27)	0.031** (8.46)
Intercept	-6.502** - (46.83)	-7.125** - (49.59)	-4.865** - (47.01)	-4.652** - (44.09)
Pseudo r-square	0.042	0.047	0.025	0.026

Note. Results presented as unstandardized coefficients and (t-values).
[†]p < .05 (one-tail test). *p < .05. **p < .01. ***p < .001. N = 3,864 tracts.

significantly associated with crime, as noted above. This finding, therefore, is misleading. As another example, in model 2 we see that a one standard deviation increase in residential instability is associated with 7% less violence ($\exp(-.020 \times 3.595) - 1 = -.069$), which also runs contrary to findings for several neighborhood classes. The finding for poverty reveals a one standard deviation increase in poverty is associated with 53% more violence ($\exp(.038 \times 11.25) - 1 = .539$).

Property Crime Results

Turning to property crime, the results in Model 3 show that *Extreme Social Disorganization* and *Moderate Social Disorganization* tracts have, on average, more property crime than *Average Neighborhoods* tracts (27% and 8%, respectively). Conversely, *Diverse Low Poverty* and *Stable Low Poverty* tracts have lower property crime rates than average tracts (9% and 14%, respectively), and *Stable Latino* tracts have 12% less property crime.

In Model 4, we adopt the traditional approach and include the neighborhood variables for comparison. As shown, tracts with more poverty and residential instability have 12% and 8% more property crime, respectively, for one standard deviation increases in each of these measures. While once again we find that the variance explained is similar across the approaches, the traditional model shows no evidence that tracts with more racial/ethnic heterogeneity have more property crime, again offering a simplistic version of reality when compared to findings from the neighborhood profiles analysis. Although there is no isolated relationship between racial/ethnic heterogeneity and property crime in model 4, the latent class with heterogeneity in the context of high poverty and instability generates very high property crime rates, whereas stability within the context of low poverty has a reinforcing negative effect on property crime rates. And whereas neighborhood poverty has a strong positive relationship with property crime in model 4, we observed that a high poverty latent class (#3) without any other disadvantaging characteristics has similar levels of property crime as the *Average Neighborhoods*. The findings thus reveal it is other characteristics of neighborhoods in concert with poverty that bring about a deleterious impact on property crime.

Ancillary Analyses

A possible critique of our approach is that we used individual measures to capture structural characteristics of neighborhoods rather than combining measures into indices to reflect “concentrated disadvantage” or “residential instability,” a common approach in the literature. The choice to include

individual measures was influenced by our desire to adhere as closely as possible to the fundamental tenets of social disorganization theory as well as create neighborhood profiles that are more easily interpretable. Still, we assessed the consequences of this by conducting additional analyses that employed such indices for concentrated disadvantage and residential instability. To compare this approach with the LCA approach, we included all individual variables used in each index in the latent class analysis (rather than the indexes themselves, since they assume the variables combine linearly). Thus, we included average length of residence and percent owners in the LCA model (from the residential instability index) and percent in poverty, single parent households, percent with at least a bachelor's degree, percent Black, and the unemployment rate (from the concentrated disadvantage index).

This approach (unsurprisingly) yielded more latent classes (14) given the greater number of variables in the LCA. Notably, the variance explained in the models using the latent class measures was effectively the same as the traditional approach of including these variables combined into indexes of concentrated disadvantage and residential instability. Moreover, only a handful of additional insights were identified by this approach, most notably that the presence of highly educated residents appears to have a significant negative impact on crime rates in some neighborhoods. Although this is a dimension that social disorganization theory did not explicitly anticipate, it may be a useful consideration for future scholarship. Nonetheless, the results overall were similar to our presented results and the analytical gains appear too small to be useful given our desire to introduce more interpretable neighborhood profiles. Still, these results suggest a possible fruitful direction for future research is to employ the LCA approach in analyses more focused on theoretical integration.⁸

Conclusion and Discussion

The goal of this study has been to challenge the variable-centered approach to studying neighborhoods and crime in the context of social disorganization theory. Despite the theory's early emphasis on the interactive nature of the structural antecedents of social disorganization, research typically considers the independent effects of key structural characteristics on crime, potentially limiting our understanding of how neighborhood ecology and crime are related. Here we adopt a "neighborhood-centered" approach. Collectively, findings reveal a broad array of neighborhood types with nuanced differences in neighborhood structure, which underscores the importance of treating communities in a holistic way. Findings also show these neighborhood types

are differentially associated with crime rates, and not always in the way the theory predicts.

The results identify nine neighborhood classes across the Southern California landscape: *Extreme Social Disorganization*, *Moderate Social Disorganization*, *High Poverty*, *Poor Latino*, *Diverse Low Poverty*, *Stable Latino*, *Homogeneous Low Poverty*, and *Stable Low Poverty*. These classes can be differentiated from an *Average* class where levels of poverty, residential instability, and racial/ethnic heterogeneity are at average levels for the region as a whole. Reviewing each class reveals widespread variation across neighborhood characteristics such as poverty, residential instability, racial/ethnic composition, age composition, family disruption, educational achievement and population density. The findings underscore broader conclusions that serve as larger take-away points from the study.

First, the findings reveal an important puzzle that deserves greater attention moving forward. Although *Extreme Social Disorganization* neighborhoods do, in fact, have higher levels of crime as the regression results reveal, neighborhoods with moderate disorganization levels do *not*, suggesting that structural disadvantage may not have the linear impact on crime that is often presumed. Why might this be the case? To some extent, this is consistent with Wilson's (1987, pp. 56–57) notion of extreme disadvantage and social isolation creating a ripple effect that results in an “exponential increase in related forms of social dislocation” and, therefore, exponentially higher levels of crime. Wilson focused primarily on economic disadvantage, and some studies measuring the poverty rate alone have *not* demonstrated the exponential effect of economic disadvantage on crime posited by Wilson (Hipp & Yates, 2011). We found here that the *combination* of poverty, heterogeneity, and instability led to much higher levels of crime in a nonlinear fashion, which may suggest a different manifestation of what Wilson proposed. It may be the combination of these structural characteristics at high levels that leads to a breakdown in informal social control—not in the monotonic linear fashion predicted by social disorganization theory but rather in a tipping point fashion.

Second, the results indicate that while poverty is an important dimension explaining levels of violence in neighborhoods—and latent classes high in poverty tended to have higher violent crime rates—its relationship with property crime is more complicated. Although poverty exhibited a strong positive relationship with property crime in the traditional approach, our high poverty latent class without any other disadvantaging characteristics did not have any more property crime than average neighborhoods. Instead, it was other characteristics of the neighborhood in concert with poverty that bring about its deleterious impact on property crime rates in extremely socially disorganized neighborhoods.

Third, residential instability was important, but in complicated ways. Some prior scholarship has hypothesized that high poverty neighborhoods with high stability do *not* benefit from residential stability, but rather stability in these neighborhoods captures the fact the residents are “trapped” in such disadvantaged communities, resulting in more crime (Warner & Pierce, 1993; Warner & Rountree, 1997). We did not, however, detect a high stability/high poverty latent class. This may be a function of our study site and the time period examined (given gentrification in recent years). Nonetheless, it is notable that such neighborhoods did not appear as a latent class in our analysis. Rather, we detected a stable *low* poverty latent class, which had the lowest levels of violent and property crime. It therefore appears that residential stability, when combined with relatively high economic advantage, leads to the sort of advantage that social disorganization theory posits, as such neighborhoods have lower crime rates. This may be because residential stability in such cases captures resident satisfaction and neighborhood attachment, as posited in systemic theory. We also found that neighborhoods with residential stability and racial homogeneity, theoretically leading to lower crime levels, in fact did not experience lower crime levels compared to average neighborhoods. In this case, such homogeneous neighborhoods were largely Latino (a more socio-economically disadvantaged group), complicating the notion of homogeneity/heterogeneity.

Fourth, how racial/ethnic heterogeneity impacts crime also appears more nuanced than originally anticipated. Although there was no isolated relationship between racial/ethnic heterogeneity and property crime in the traditional approach, the neighborhood-centered approach revealed that a latent class with heterogeneity in the context of high poverty and instability has very high crime rates. In contrast, a high diversity neighborhood with low poverty levels actually had lower crime rates. Although social disorganization theory predicts that heterogeneity reduces social networks and therefore limits cohesion, it may be that heterogeneity does not operate in this way in a context of economic advantage; rather, racial/ethnic heterogeneity may only have negative consequences in the presence of other structural disadvantages.

Finally, the field’s (largely) singular interest in socially disorganized neighborhoods, evidenced by simultaneously high levels of poverty, residential instability and racial/ethnic heterogeneity, may be misguided. In fact, the prototypical “disorganized neighborhood” is a rare occurrence, at least in our sample. Evidence for this is seen in the number of neighborhoods that fall within the different classes. Whereas *Extreme Social Disorganization*, the prototypical socially disorganized neighborhood class, comprised only a few cases (just 1.2% of tracts), far more neighborhoods comprise the less-acute *Moderate Social Disorganization* class (12.7%) and the mixed constellation

exhibited by *High Poverty Neighborhoods* (13.5%). Broadening the focus—both theoretically and empirically—beyond prototypically socially disorganized neighborhoods will help better align research with reality.

The findings must be interpreted within the context of study limitations. First, the data were cross-sectional, limiting our understanding of how these neighborhoods evolve over time based on these structural characteristics, suggesting an important direction for future research. Second, we were limited to studying neighborhoods in a single region. Although this is common in the neighborhoods and crime literature, it is critical for future studies to utilize a neighborhood-centered approach in other settings where the long-term trajectory of impoverished neighborhoods may differ from that of southern California (Small et al., 2018), and may therefore yield differences in the latent classes detected. Third, given various clustering algorithms available, there is no guarantee that different strategies will yield similar results. Although we utilized a popular technique with desirable properties, the relative indeterminacy of all clustering techniques should be kept in mind. Fourth, while our choice to emphasize the theory's original framing and to include individual measures in the main analysis is influenced by the desire to adhere as closely as possible to the fundamental tenets of social disorganization theory and to create neighborhood profiles that are more easily interpretable, it ignores important developments that characterize the theory today. Future research should focus on applying the neighborhood-centered approach to a more contemporary version of social disorganization theory. Finally, without proper data (e.g., survey data), we are unable to determine the degree to which the neighborhood-centered approach helps us better understand the theoretical mechanisms underlying the relationships between traditional social disorganization measures and crime. This, too, awaits future inquiry.

In closing, we suggest that scholars would be well-served to consider adopting a neighborhood-centered approach in future research. Our results highlight that such an approach can provide insights not apparent in the more common variable-centered approach. Although our goal was to unpack further insights within social disorganization theory, future work focused on theory integration may wish to include more of the measures from the models in the clustering routine. We further argue that a neighborhood-centered approach is theoretically more consonant with how neighborhoods actually operate, as they tend to be bundles of attributes rather than independent characteristics that can be manipulated on their own. The fact that some of the “bundles” of structural measures exhibited relationships with crime that were inconsistent with some tenants of social disorganization theory implies this approach may generate new theoretical insights moving forward.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. Given our variables are continuous, this analysis is sometimes referred to as latent profile analysis (LPA). This nomenclature refers to an older estimation tradition and is unimportant in that researchers can estimate models with continuous and categorical variables, blurring the distinction between LCA and LPA. Therefore, the more general term is LCA and both techniques have the assumption of a lack of correlation between the variables once conditioning on group membership.
2. In that study, funded by the National Institute of Justice, researchers contacted police agencies in the Southern California region and requested address-level incident crime data for the years 2005 to 2012. Across all cities in the region, 61.8% have crime data for all or seven of the 8 years in this range. For remaining cities, coverage varies year to year. The data come from crime reports officially coded and reported by police departments, which were later classified into six Uniform Crime Report (UCR) categories: homicide, aggravated assault, robbery, burglary, motor vehicle theft, and larceny. Crime events were geocoded for each city separately to latitude–longitude point locations using ArcGIS 10.2 and aggregated to various units such as blocks, block groups, and census tracts. The average geocoding match rate was 97.2% across cities, with the lowest rate at 91.4%. SCCS data have been used in prior studies (Branic & Kubrin, 2018; Hipp & Kubrin, 2017; Kubrin & Hipp, 2016).
3. A long-debated issue is whether census tracts constitute neighborhoods. Tracts generally have stable boundaries and are designed to be relatively homogenous with respect to population characteristics, economic status, and living conditions. Although imperfect, tracts as proxies have been used in many neighborhood effects studies (Sampson et al., 2002, p. 445).
4. We exclude rape from the analyses due to reporting issues.

5. The BIC for the nine-class model was 92,906, an improvement on models with fewer classes (e.g., BICs for the seven- and eight-class models were 92,948 and 92,926, respectively). Moreover, classes in the nine-class solution were substantively meaningful. Although the BIC was slightly better in the 10-class solution (92,892), there was redundancy in the classes, indicating the model did not offer unique information.
6. City boundaries in a region such as southern California are often relatively arbitrary. Thus, whereas our models allow comparisons of neighborhoods across different cities (e.g., Beverly Hills vs. Compton), we argue this is no different than studies of large cities such as Chicago or Los Angeles that compare neighborhoods from very different parts of the city. In fact, such variability is presumably precisely what the researcher is interested in.
7. We compute z -scores using the formula: $[(\text{class mean}(\text{var}) - \text{grand mean}(\text{var})) / \text{grand standard deviation}(\text{var})]$.
8. For additional information and findings from these analyses, please see the Supplemental Appendix 1.

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