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Violent Injury and Neighborhood Racial/Ethnic Diversity in Oakland, California

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Abstract Racial and ethnic segregation has been linked to a number of deleterious health outcomes, including violence. Previous studies of segregation and violence have focused on segregation between African Americans and Whites, used homicide as a measure of violence, and employed segregation measures that fail to take into account neighborhood level processes. We examined the relationship between neighborhood diversity and violent injury in Oakland, California. Violent injuries from the Alameda County Medical Center Trauma Registry that occurred between 1998 and 2002 were geocoded. A local measure of diversity among African American, White, Hispanic, and Asian populations that captured interactions across census block group boundaries was calculated from 2000 U.S. Census data and a Geographic Information System. The relationship between violent injuries and neighborhood level of diversity, adjusted for covariates, was analyzed with zero-inflated negative binomial regression. There was a significant and inverse association between level of racial and ethnic diversity and rate of violent injury (IRR 0.30; 95% CI: 0.13–0.69). There was a similar relationship between diversity and violent injury for predominantly African American block groups (IRR 0.23; 95% CI: 0.08–0.62) and predominantly Hispanic block groups (IRR 0.08; 95% CI: 0.01–0.76). Diversity was not significantly associated with violent injury in predominantly White or Asian block groups. Block group racial and ethnic diversity is associated with lower rates of violent injury, particularly for predominantly African American and Hispanic block groups.

Keywords Segregation · Social determinants of health · Violent injury · Neighborhood

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Introduction

The USA has a long and ignominious history of racial residential segregation [1–3], which Douglas Massey defines as the "degree to which two or more groups live separately from one another, in different parts of the urban environment." [4] Massey and others argue that segregation inevitably concentrates poverty in African American neighborhoods, with disastrous effects on employment [5], education [6], home ownership [7], and other aspects of community life. These are the very same factors that figure prominently in the leading sociological theories on the origins of community violence [8–10]. For example, social disorganization theory proposes that communities that have high rates of destabilizing forces like poverty, housing instability, and single parent households lose the ability to assert control over their members through supervision of teenagers, friendship networks, and community organizations [11]. Other theories [9, 12] on violence highlight potential cultural factors and the effects of both absolute and relative economic deprivation. The societal consequences of segregation are central in all three of these theories, thus providing a theoretical link between segregation and violent injury.

There is a large body of literature on the relationship between residential segregation and health outcomes [13–15] and its association with violence in particular [16–39]. In general, studies have found positive and significant associations between residential segregation and violent crime. While the findings are relatively consistent, previous studies suffer from a number of important limitations. First, with a few exceptions [30, 35, 40], most previous studies use crime data, particularly homicide rates, to measure violence. However, this reliance on homicide as the outcome focuses on the most severe form of violence, ignores violence that differs from homicide by fractions of inches, and limits sample size. Secondly, most studies use cities as the unit of analysis. The few studies that use a smaller level of aggregation like zip codes, census tracts, and block groups [19, 21, 25, 31, 33, 36–38] point to a number of flaws in using cities as the unit of analysis. For example, racial composition, rates of violence, and mediating factors such as poverty vary widely within cities. Aggregating to the city level obscures these differences and makes it impossible to study true neighborhood effects [41, 42]. Just one study mentions the potential for spillover effects from adjacent neighborhoods [37]. Thirdly, studies generally examine segregation between African Americans and Whites [13, 15, 42]. With a few exceptions [25, 33, 37–39, 41], other racial and ethnic groups are not considered. Finally, studies generally define residential segregation with two widely used measures of citywide segregation: the dissimilarity and interaction indices. Both measures use neighborhood level data like census tracts to calculate a citywide index. These indices have been criticized on a number of fronts [43–47], including their assumptions that census tract boundaries are good reflections of social boundaries and that peoples' interactions end at these artificially constructed lines. As Michael White [43] and David Wong [44] point out, segregation measures, at a basic level, should reflect interactions between people, and to assume that interactions end at neighborhood boundaries ignores reality.

These limitations argue for an analysis of the relationship between racial residential segregation and violent injury at the neighborhood level that takes into account multiple ethnic and racial groups and their interactions across census boundaries. Oakland, California was chosen as a study location because it is an ethnically and racially heterogeneous city (Table 1) and thus provides an ideal counterpoint to studies that focus on cities without large Hispanic and Asian communities. Oakland also has a relatively high rate of violent crime in comparison to the USA, California, and other cities in Alameda County [48]. Violent crime in Oakland is heavily concentrated in a few areas of the city [49], which suggests that violent injuries might be similarly distributed in space. Finally, in Oakland, all of the major violent injuries are treated at one hospital, the Alameda County Medical Center—Highland Campus, that maintains a detailed trauma registry.

Methods

Violent Injuries by Block Group

In October of 2009, the trauma registrar at the Alameda County Medical Center—Highland Campus (ACMC–Highland) abstracted violent injuries from their registry that occurred between January 1, 1998 and December 31, 2002 and that had *International Classification of Diseases*, *Ninth Revision, Clinical Modification* (ICD-9) codes between E960 and E969 [50]. As Oakland's designated trauma center, the registry includes injuries of people who are directly transported, transferred, or who self-present to ACMC–Highland and meet criteria for referral to the trauma service. It excludes minor trauma

Table 1 Distribution of Races and Ethnicities in Oakland, California, 2000

Non-Hispanic African American	36.8%
Non-Hispanic White	23.2%
Hispanic of all races	22.2%
Asian	16.5%

from both ACMC–Highland as well as those that present to other local hospitals. The date range was selected to decrease the effects of yearly variation in violent injuries and to select a period of time that would reasonably correspond to demographic information from the 2000 U.S. Census. ICD-9 E-Codes 960–969 include "Homicide and Injuries Inflicted by Another Person" and correspond to the definition of violent injury used in previous research [30, 35]. Injury locations were provided to the registry by the Emergency Medical Technicians who responded to 911 calls. Addresses with sufficient geographic information were geocoded in ArcMap (ESRI, Version 9.3.1) using the Street Addresses U.S. Address Locator (ESRI) and linked to demographic data by block group from the 2000 U.S. Census to determine the number of violent injuries per block group.

Spatial Diversity

A local measure of diversity known as entropy, as adapted by David Wong, was selected to measure multi-group segregation at the block group level [45]. Wong's measure has several strengths, including being simple to calculate, bounded by zero and one, adaptable to the inclusion of multiple groups, interpretable at small units of aggregation such as census tracts and block groups, and being relatively easy to transform into a spatial version incorporating neighboring block groups. Previous studies of local (i.e., block group or census tract level) segregation [16, 18, 19, 21, 25, 31, 33, 41] have primarily used neighborhood composition (for example percent African American), which does not account for multiple groups. One study included information from neighboring block groups using an original measure of racial segregation [36]. However, this measure failed to meet many of the favorable characteristics of Wong's measure discussed above. We chose block groups as the unit of analysis because on visual inspection, unlike other geographic units with associated census data, they corresponded relatively well to a common, walkable neighborhood definition of a quarter-mile radius after we incorporated them with neighboring block groups [51]. Additionally, researchers have reported that smaller neighborhood units provide a more meaningful and exact estimate of area effects [52], and block groups are the smallest census area with associated demographic information.

Wong derives the spatial measure of diversity that takes into account neighboring block groups from a similar, aspatial measure that only considers the block group of interest. Wong describes the calculation of this aspatial diversity measure as shown in Eq. 1 [45]. Equation 2 shows this diversity measure if one were to consider the diversity between African Americans, Whites, Hispanics, and Asians in a particular block group. The measure ranges from zero to one, with one representing maximum diversity and signifying that all groups are represented in equal proportions in the areal unit. To include interactions across census boundaries, Wong suggests redefining each block group to include all block groups that share a border with it, creating a "composite neighborhood." The spatial version of the diversity measure, H^*_i is shown in Eq. 3. Figure 1 illustrates how these composite populations were calculated. Group A was associated with all of its neighbors in ArcMap first by creating a buffer to capture all neighboring block groups. This is analogous to drawing the black box in Fig. 1, which can be done simultaneously for all block groups in ArcMap. The intersect tool was then used to identify each block group with itself (A) and neighboring groups (B, C, D, E, F, G, H, I). In Stata 10 (Intercooled) this newly defined composite neighborhood was merged with demographic information and collapsed by block group, giving the composite population counts used in Eq. 3.

$$H_i = \frac{-\sum_{k=1}^{n}\left[\left(\frac{P_k}{P}\right) ln\left(\frac{P_k}{P}\right)\right]}{ln\, n} \tag{1}$$

Where H_i is the measure of diversity in block group i; n identifies the number of ethnic or racial groups in question, P identifies the total population in i, and P_k identifies the population of group k in i.

$$\frac{-[\%\text{African American}^{*}\ln(\%\text{African American})] + [\%\text{white}^{*}\ln(\%\text{white})] + [\%\text{Hispanic}^{*}\ln(\%\text{Hispanic})] + [\%\text{Asian}^{*}\ln(\%\text{Asian})]}{\ln 4} \tag{2}$$

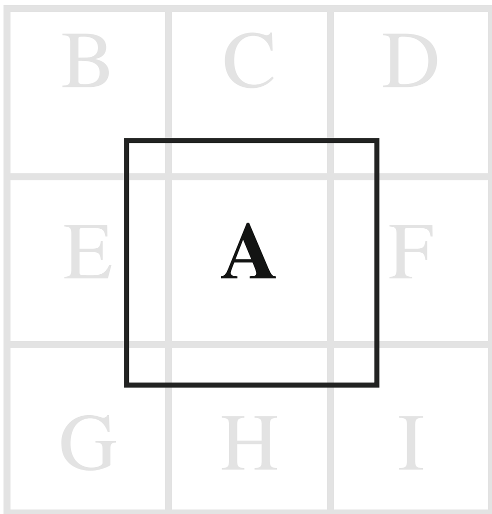

Fig. 1 Schematic representation of block group A and surrounding block groups B through I. The dark square represents a boundary drawn to capture the influence of the surrounding block groups

$$H^*_i = \frac{-\sum_{k=1}^{n}\left[\left(\frac{CP_k}{CP}\right) ln\left(\frac{CP_k}{CP}\right)\right]}{ln\, n} \tag{3}$$

Where H_i^* is the measure of composite diversity in block group i; population counts as described in Equation 1 are replaced by composite neighborhood counts of populations of various racial/ethnic groups (CP_k) and total population (CP).

Census and Control Variables

All census information was downloaded in November 2009 from the U.S. Census' American FactFinder website using the custom tables feature for Summary File 3. The variables included in the spatial diversity measure were the block group populations of non-Hispanic Whites, non-Hispanic African Americans, non-Hispanic Asians, and Hispanics. Based on previous research, potential confounders were identified that may affect both the likelihood of injury and level of diversity at the block group level: total population; percentage below the 1999 federal poverty level; proportion of female-headed households; proportion of residents who were 25 years old and over who had not graduated from high school; proportion of housing units with five or more units; proportion of the population between 15 and 24 years old; proportion of residents who were male; and proportion of the civilian labor force that was unemployed.

Statistical Analysis

Like most count data, the distribution of the number of violent injuries per block group is highly skewed, making ordinary least squares regression a poor choice for the analysis. Count data are better modeled by either Poisson or negative binomial regressions. In this study, the variance in number of violent injuries per block group (49.29) was higher than the mean (6.54), indicating that the data were overdispersed and that negative binomial models were more appropriate. We adjusted for the preponderance of block groups without injuries (18%) by using a zero-inflated model. In the zero-inflated models below, we hypothesized that excessive zeros (i.e., zeros above what one would expect in a negative binomial distribution) would be predicted by economic factors and used percentage unemployment as the inflation factor, although we obtained similar results from using the percentage in the neighborhood under 200% FPL. Model diagnostics confirmed that a negative binomial model was more appropriate than Poisson regression and that a zero-inflated model was more appropriate than a non-zero-inflated model [53, 54].

The diversity measure used for this study does not distinguish by the predominant race/ethnicity: a neighborhood that is 91% White, 3% Asian, 3% Hispanic, and 3% African American would have the same diversity score as a neighborhood that is 91% African American, 3% White, 3% Asian, and 3% Hispanic. To see how diversity's relationship with violent injury changed depending on the predominant race/ethnicity, our data were stratified by this factor. To achieve mutually exclusive divisions, predominance was defined as having a simple majority in a composite block group.

The study received administrative review by the Alameda County Medical Center Human Subjects Protection Committee.

Results

Sample

The original sample included the 338 block groups within the border of Oakland, California. Because of the primary interest in the effects of social interactions, 7 block groups were excluded with populations less than 100, leaving a final sample of 331 block groups. These excluded block groups were comprised of the Port of

Oakland, a sports complex, industrial areas, parks, and other open spaces.

Violent Injuries

The original data abstraction from the Alameda County Medical Center trauma registry included 3392 injuries that met the date and ICD-9 inclusion criteria. Of those, 2353 (69%) injuries were suitable for geocoding. After restricting to injuries that occurred in Oakland, the final sample included 2164 injuries (64% of the injuries from the original data abstraction). These injuries were similar to the 3332 originally abstracted injuries in their distribution of race/ethnicity, sex, and age of the victim.

Descriptive Statistics

Table 2 shows descriptive statistics for the variables. The number of violent injuries from the trauma registry in each block group between 1998 and 2002 ranged from a minimum of 0 to a maximum of 35, with a mean of 6.54 (SD, 7.02). There were 60 block groups (18%) without any violent injuries recorded in the trauma registry. The level of composite diversity ranged from a minimum of 0.38 to a maximum of 0.99, with a mean of 0.77 (SD, 0.13). A map showing the distribution of violent injuries and composite diversity in the block groups in the study is shown in Fig. 2.

Negative Binomial Regression

In the negative binomial regression model (Table 3), population was controlled for by specifying it as the exposure factor. The number of violent injuries per block group was regressed on composite diversity and the a priori covariates. In our zero-inflated model, increasing composite diversity by 1 unit decreases the rate of violent injury by a factor of 0.30 (95% CI 0.13–0.69), adjusting for covariates and excessive block groups with zero injuries. In other words, across all block groups in Oakland an increased level of composite diversity is significantly associated with a decreased number of violent injuries.

Stratification

To assess whether this relationship differed depending on the predominant racial/ethnic group in the block group, the analysis was stratified by predominant race/ethnicity within the composite block group. Results are shown in Table 4 for African American and Hispanic block groups. For the 122 predominantly African American composite block groups, the relationship between diversity and violent injury (IRR = 0.23; CI: 0.083–0.62) was similar in magnitude, direction, and significance to the non-stratified model. Similarly, in the 53 predominantly Hispanic composite block groups, a significant inverse relationship between composite diversity and violent injury (IRR = .08; 95% CI: 0.01–0.76) was observed. The 37 predominantly Asian neighborhoods and 99 predominantly White block groups showed non-significant relationships for diversity and injury. Similar results were obtained when the predominant group was determined without taking neighboring block groups' populations into consideration.

Discussion

Our results indicate that when we adjust for block groups with zero injuries, increased levels of diversity

Table 2 Descriptive statistics for 331 Oakland block groups

	Minimum	Maximum	Mean	Standard deviation
Number violent injuries	0	35	6.54	7.02
Composite diversity	0.38	0.99	0.77	0.13
Female-headed households (%)	0.0	79.9	31.3	15.8
Non-high school graduates (%)	0.0	76.2	27.7	18.9
Housing units of 5 or more (%)	0.0	100.0	24.1	25.4
Male population (%)	10.6	77.8	47.8	5.0
Population aged 15–24 (%)	0.0	70.3	13.3	6.1
Unemployed (%)	0.0	41.5	9.4	7.1
Under the 1999 federal poverty line (%)	0.0	59.3	18.9	12.9

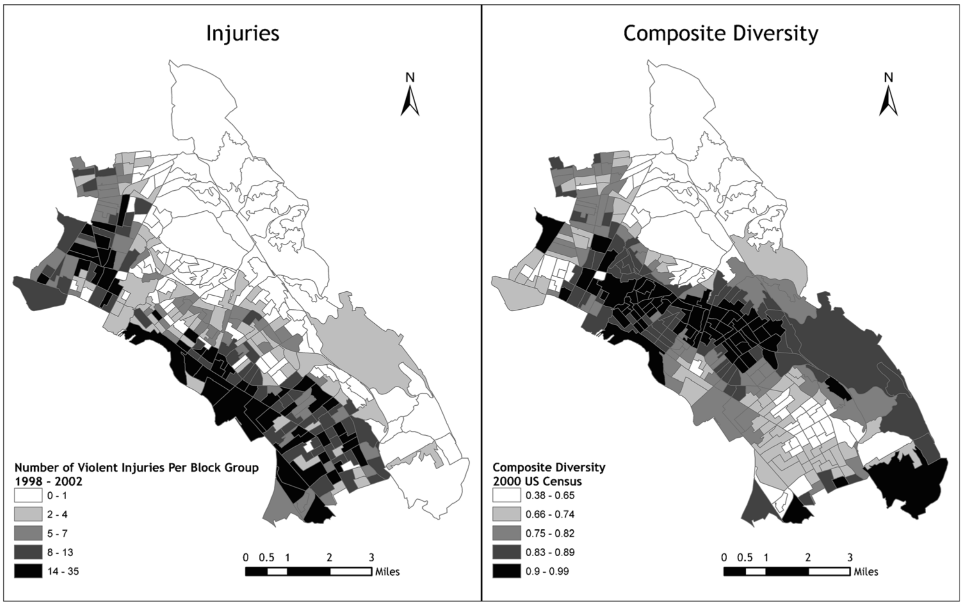

Fig. 2 The variables on violent injuries and composite diversity are divided into quintiles represented by darkening shades of gray. Darker colors indicate higher levels of injury and composite diversity, respectively

are associated with lower levels of violent injury in block groups in Oakland, California. The results from the stratified models suggest that the association between diversity and injury is strongest for both African American and Hispanic block groups. In contrast, diversity was not found to be associated with injury for predominantly White or Asian block groups. One possible explanation for these results is the relatively narrow range (0 to 13), low mean (1.22), and low standard deviation (2.04) of the number of violent injuries in predominantly White composite block groups. Along the same lines, there were only 37 predominantly Asian block groups with a relatively low mean (5.54) number of injuries.

Table 3 Incidence rate ratios for violent injury according to block group composite diversity and demographic characteristics

	Zero-inflated negative binomial regression	
	IRR	(95% CI)
Composite diversity	0.30**	(0.13–0.69)
Female-headed households	4.86**	(2.13–11.07)
Non-high school graduates	9.54**	(4.60–19.78)
Housing units of 5 or more	1.53*	(1.02–2.31)
Male population	9.37*	(1.25–70.07)
Population aged 15–24	1.21	(0.17–8.50)
Unemployment	8.09**	(1.84–35.77)
Poverty	1.53	(.54–4.37)
Number of block groups	331	

IRR incidence rate ratio, *CI* confidence interval

$^*p < 0.05$, $^{**}p < 0.01$

Contributions

This study is consistent with a large body of research suggesting that lower levels of segregation (in this case higher levels of diversity) are associated with lower levels of violence. It is also consistent with reports of differential effects of segregation on African American and Hispanic groups [38, 39]. This work addresses many of the limitations in the field by studying injury rather than crime, incorporating Asian and Hispanic populations, and using a measure at the neighborhood level that takes into account interactions across census borders. These approaches have been used or suggested in previous work, but had not been combined in one study.

The findings are also consistent with many of the conceptual underpinnings regarding the mechanisms by which segregation may be detrimental to communities [1, 55], but challenge the tenet of social disorganization theory that ethnic heterogeneity is a destabilizing force [9, 11]. Within the literature on diversity, there is some debate as to how diversity affects levels of neighborhood

Table 4 Incidence rate ratios for violent injury stratified by predominant race/ethnicity

	Predominantly African American block groups		Predominantly Hispanic block groups	
	IRR	(95% CI)	IRR	(95% CI)
Composite diversity	0.23**	(0.083–0.62)	0.08*	(0.01–0.76)
Female-headed households	3.47*	(1.32–9.09)	0.39	(0.37–4.03)
Non-high school graduates	4.31**	(1.61–11.48)	1.57	(0.22–11.15)
Housing units of 5 or more	2.21**	(1.23–3.96)	1.77	(0.44–7.17)
Male population	12.29*	(1.05–143.06)	10.6	(0.08–1423.7)
Population aged 15–24	1.48	(0.15–14.4)	0.05	(0.0002–11.63)
Unemployment	6.90*	(1.52–31.26)	12.04	(0.51–11.63)
Poverty	1.18	(0.36–3.91)	0.74	(0.08–7.18)
Number block groups	142		53	
Minimum–maximum number of violent injuries	0–35		1–28	
Mean number violent injuries (standard deviation)	8.37 (6.96)		12.24 (8.01)	

IRR incidence rate ratio, *CI* confidence interval

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

trust. For example, Robert Putnam argues diversity, at least in the short term, can lead people to “hunker down” and withdraw from the community [56]. Following this line of reasoning, lower rates of violence in diverse neighborhoods may be the result of decreased social interactions. On the other hand, if diversity fosters neighborhood trust [57], that could be one of the driving forces behind lower rates of violence in those communities. Despite the lack of research on associations between racial and ethnic diversity and violent injury, these results are consistent with a recent paper on language diversity and homicide rates [58].

Limitations and Directions for Further Research

As with all cross-sectional and ecologic data, it is important to note that the associations found do not necessarily imply causality. Neighborhoods with high rates of violent injury may attract a less diverse population, rather than low levels of diversity leading to high levels of violence [59]. We also selected our model based on conceptual rather than data-driven attributes; nevertheless, our control variables may have been collinear. Our results cannot be extrapolated beyond Oakland; the effects of diverse neighborhoods may be different in other cities. In addition, there are other measures of diversity and integration used in the sociologic literature [60] that may have yielded different results.

Although model selection statistics showed that a zero-inflated model was appropriate, conceptually this might not be the case. Zero-inflated models are designed for situations where observations with counts of zero may come about through different processes than observations with counts of 1 or more. In our case, a zero-inflated model would be conceptually appropriate if we believed that we observed no injuries in certain block groups because people in that block group were going to another hospital for treatment, for example. To check the model, we ran a non-zero-inflated model for all block groups, and the association between composite diversity and injury disappeared, however it returned when we only included the 271 block groups with at least 1 injury (results not shown). This suggests that our results hold when controlling for block groups with zero injuries, whether through zero-inflated modeling or by excluding those block groups.

Many of our limitations derive from the definition of a neighborhood. To define the composite diversity measure, neighborhoods were identified as a block group of interest plus those block groups that shared a border with it. However, different criteria for a composite block group could have been used, like distance from the block group of interest [45], or even by estimating potential interactions at a level closer to that experienced by individuals [46]. While a composite definition of a neighborhood was used to calculate our diversity measures, that definition did not apply to our other variables.

This assumed that the effects of interactions between races could occur across boundaries, but that the effects of poverty, unemployment, and other covariates remained within boundaries. Finally, despite the fact that the data had a spatial component, there was no adjustment for the fact that neighborhoods that are closer to each other are similar due to their proximity (i.e., spatial autocorrelation). However, because one of the primary interests of the study was to capture the effects of neighboring block groups in the diversity measure, adjusting for autocorrelation would have been contrary to one of the purposes of the study. Nonetheless, spatial effects may have biased our estimates.

The sample of violent injuries was subject to a number of potential biases. Some addresses necessitated manual assignment, with injuries occurring in areas familiar to the investigator thus possibly having a better chance of being assigned an accurate address. This study could not consider those in the trauma registry without an address of injury, which may have underestimated injuries closer to the medical center. Also, the sample did not include pediatric violent injuries. Furthermore, the trauma registry did not include minor violent injuries and those that presented to other hospitals and were not severe enough to require a transfer to the trauma center, although as mentioned above, statistical procedures may have controlled for associated biases when they resulted in a block group without injuries. In an era where GIS software is widely available, part of public health injury surveillance should focus on obtaining accurate addresses of events whenever it is possible and does not infringe on patients' privacy.

Dolores Acevedo-Garcia criticizes studies of segregation and health for failing to tie to conceptual frameworks linking segregation and particular health outcomes [13]. Future studies of segregation and violent injury could include more sophisticated measurements of family instability, participation in community institutions [32], and youth supervision, all of which are thought to be associated with rates of violence in a community [9, 11] and are also consequences of racial segregation [1]. Along the same lines, future research should examine the effects of economic segregation, which could have confounded our results and plays a crucial role in communities [61, 62]. Acevedo-Garcia further criticizes studies for not incorporating multilevel modeling techniques. Future research could collect injury data from multiple cities and follow Krivo and Peterson's work using crime data [41]. Finally, our finding of no association between diversity and violence in Asian-American neighborhoods calls for further examination. By incorporating these suggestions, we can move closer to understanding the complicated interactions between race, place, and health outcomes. Results from this line of research can help elucidate the processes underlying health disparities and inform policy decisions that will promote vibrant, safe, healthy neighborhoods.

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