

Socioeconomic Disadvantage and Homicide: A Spatial Ecological Case-Control Study of US ZIP Codes

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Abstract

Background: Homicide is a major cause of death and a determinant of health disparities in the United States. This burden overwhelmingly affects people from racial and ethnic minority populations as homicide occurs more often in neighborhoods with high proportions of racial and ethnic minority residents. Research has identified that social and physical environmental conditions contribute to variation in homicide rates between neighborhoods; however, it is not clear why some neighborhoods with high concentrations of racial and ethnic minority residents have high homicide rates while neighborhoods with similar demographic compositions do not. The aim of this study was to assess whether relative socioeconomic disadvantage, (i.e., income inequality), or absolute socioeconomic disadvantage (i.e., income) measured at the ZIP code- and state-levels, is associated with high homicide rates in US neighborhoods, independent of racial and ethnic composition.

Methods: This ecological case-control study compared median household income and income inequality in 250 ZIP codes with the highest homicide rate in 2017 (cases) to 250 ZIP codes that did not experience any homicide deaths in 2017 (controls). Cases were matched to controls 1:1 based on demographic composition. Variables were measured at both the ZIP code- and state-levels.

Results: Lower median household income at the ZIP code-level contributed most substantially to the homicide rate. Income inequality at the state-level, however, was additionally significant when controlling for both ZIP code- and state-level factors.

Conclusions: Area-based interventions that improve absolute measures of neighborhood socioeconomic disadvantage may reduce gaps in homicide rates.

Background

Violent death—including homicides and suicides—is a leading cause of mortality and a major contributor to health disparities in the United States. A total of 67,299 people were killed in violent incidents in 2017, including 19,510 from homicide (1). Risks for homicide are greater for men (2, 3), adolescents and young adults (2), and Black and Hispanic people (4, 5). Homicide is the leading cause of death for black men aged ≤ 44 and is a major contributor to differences in life expectancy between White and Black men (6). Identifying conditions that contribute to the occurrence of homicide is an essential step towards developing effective preventive interventions that reduce the absolute health burden and socio-demographically structured health disparities.

Many decades of theory and empirical evidence identify that neighborhood social environmental conditions are important determinants of violent crime and could therefore be candidates for intervention. For instance, early theories of criminology described human behavior as the result of conscious processes, wherein rational actors weigh prospective costs and benefits of carrying out crime (7). From this perspective, violent crime (assault, homicide, rape, and robbery) can be understood as a solution to an optimization problem (8). The prospective costs of choosing to act violently include injury to oneself,

imprisonment, loss of future conventional opportunity; conversely the prospective benefits include settling a grievance, winning access to a resource, enhanced social capital (within some cultural contexts) (9). This explanation of the etiology of individual violent events can be expanded to explain observed distributions of violence within and between populations. The costs of violence typically outweigh the benefits, so violence is a statistically rare event, occurring in only a small proportion of human interactions; but reduced access to social, physical, and economic resources can tip the balance in favor of violence. By definition, access to such resources is more limited for disadvantaged populations and in disadvantaged neighborhoods, and when disadvantaged people conceive such disparities as “losses” they are even more likely to engage in risk-seeking behaviors such as violent crime (10).

An important addendum to rationalist explanations of violent crime is that environmental characteristics, whether at the city, state, or national level, are powerful predictors of violent crime (11–13). There is a growing literature base arguing that indices of relative socioeconomic disadvantage, such as income inequality, are strong predictors of crime (14, 15). Several theories have attempted to explain this relationship between income inequality and violent crime (11, 16). One of the initial hypotheses by Shaw and McKay (1942) stated that concentration of poor economic conditions lead to social disorganization through a breakdown of social cohesion. Social disorganization theory suggests that a person’s residential location is more significant than the person’s characteristics when predicting criminal activity. Moreover, inequality and the concentration of poor economic conditions lead to social disorganization through a breakdown of social cohesion and norms. When these economic inequalities are associated with ascribed characteristics such as race, latent animosities and a situation characterized by social disorganization is created (11). The consequence is socially structured inequalities that result in feelings of “resentment, frustration, hopelessness, and alienation” which the theory suggests leads to widespread social disorganization and violent crime (11).

Empirical studies generally support these theoretical predictions regarding geographic distributions of violent crime. Research identifies that violent crime, including homicide, concentrates in specific neighborhoods (17, 18). For example, 74% of crimes in Boston occurred in 5% of city blocks (17). In Seattle, crime reduction was due mostly to crime declines in a small group of street segments (19). More recently, researchers have demonstrated that the concentration of crime at particular places is stable over time (17, 19). A wide range of physical and social environmental conditions are associated with violent crime incidence in small areas (20, 21). Violence is higher in communities where there are limited economic opportunities; where there are high concentrations of poor and unemployed people; and where there is greater residential instability (22). One study found remediation of abandoned buildings in Philadelphia significantly reduced firearm violence as did vacant lot remediation (23). Abandoned buildings and vacant lots can serve as out-of-sight staging or storage areas for illegal firearms until they are needed (24).

With substantial evidence that economic disadvantage drives crime, a fundamental debate remains on whether it is relative socioeconomic disadvantage (i.e., income inequality) or absolute socioeconomic

disadvantage (i.e., income) that is indeed the driver of the relationship. The argument linking income inequality and violent crime differs because income inequality is not an aggregate variable like poverty. The connection between poverty and violent crime is resource deprivation. Moreover, resource deprivation or “material disadvantage” causes frustration which can result in violent aggression (10). Disentangling the contribution of income and income inequality from the multiple potential confounders, including the demographic composition of the resident population, is a methodologically complex problem. Further, a social ecological systems perspective—the dominant theoretical framework that guides much epidemiologic research in neighborhoods and health (25, 26)—suggests that determinants of homicide will also be multi-scale and dynamic, and will reflect fundamental macrosocial causes of structural disadvantage that increase risk for crime and violence. For example, neighborhoods with high rates of poverty and income inequality will be related to distal social and economic policies at county, state, and federal levels. In addition, the strength of state-level measures of poverty and income inequality may affect crime in local areas. The extent to which local and state-level measures of relative and absolute measures of socioeconomic disadvantage are associated with homicide is poorly understood.

The aim of this study was to identify whether income or income inequality at the ZIP-code or state-level contribute to homicide in small areas, operationalized as US ZIP codes. A matched ecological case-control design allowed us to address problems related to various highly correlated confounders, and to examine why some neighborhoods with high concentrations of racial and ethnic minority residents have high homicide rates while other such neighborhoods do not experience homicide.

Methods

Study Design

The units of analysis for this ecological case-control study were 2017 ZIP codes. We chose ZIP codes as the unit of analysis in part because of data availability but additionally because of within-neighborhood heterogeneity in alternate geographies such as census tracts. Furthermore, place-based interventions may be easier to implement at the ZIP code-level. ZIP codes eligible for inclusion were in the 34 US states and four counties in California that participated in the National Violent Death Reporting System (NVDRS) during that year (n = 23,949). The Centers for Disease Control and Prevention (CDC) created the NVDRS in 2002 to collect data on all types of violent deaths—including homicides and suicides—in all settings for all age groups (27). The NVDRS has been fully described elsewhere (28). Abstractors in participating states extract detailed information from the death certificate, coroner or medical examiner’s report, and police report to summarize violent deaths. Available data are victim demographic characteristics, weapons, suspects, victim–suspect relationships, location, and precipitating circumstances. The abstractor assigns a “type of death” code to the case and writes two brief narratives on each incident to summarize the coroner or medical examiner report and the police report.

We used the NVDRS to calculate counts of homicide for 2017 within eligible ZIP codes. Case units were the 250 ZIP codes that had the highest homicide rate and had ≥ 5 homicides in 2017 (to ensure the rate

was stable). Controls were ZIP codes that had no homicides in 2017 (29), frequency matched to cases at a ratio of 1:1. The matching procedure was performed using American Community Survey (ACS) 2013-2017 5-year estimates for ZIP Code Tabulation Areas (ZCTAs) (30). We calculated a balanced matrix of the Euclidean distance in 6-dimensional space between all eligible ZIP codes based on 6 demographic characteristics identified in prior studies to be associated with increased homicide rates: proportion Black, proportion Hispanic, proportion Asian, proportion male, proportion aged 15 to 24, and proportion aged 25 to 34 (31, 32). Cases were matched to the eligible control that was closest in Euclidian distance, located in a different state, and contained the same USDA Rural-Urban Continuum Code classification (urban, micropolitan, small town, or rural). This procedure ensured that cases were the most demographically similar to their corresponding control from among all ZIP codes in the 34 states and four counties in California participating in the NVDRS in 2017, while allowing assessment of associations for both ZIP code-level and state-level exposures. The total analytic sample was 500 ZIP codes. The reason for this sample was a trade-off between feasibility and statistical power as there was an intensive data collection component.

ZIP Code-Level Measures

We measured two independent variables at the ZIP code-level differentiating between income and income inequality. We used ACS 2013-2017 5-year estimates to obtain median household income and the GINI coefficient for each ZIP code. The GINI coefficient, though documented with limitations, has become a standard measurement of income inequality (30). It ranges from zero, expressing perfect equality (where all persons have equal shared of aggregate income), to one, expressing maximal inequality (where one person has all the income and the rest have none). The measurement characterizes the distribution of income within a social unit or group of people and therefore has no individual level analogue.

Other independent measures at the ZIP code-level we controlled for included population size, population density, percent of the population that was unemployed, percent land use (proportion industrial, retail, and green space) (33), and walkability. We measured population density as population per km² using the ACS 2013-2017 5-year estimates (30). We used county parcel files provided by the US Census Bureau to calculate percent of land area that is retail, industrial, and green space (34). To assess walkability, we used the walk score provided by WalkScore™ (35). Walk scores range from 0 to 100. Values closer to 0 signify car dependent ZIP codes and increasing values correspond to increasing walkability.

State-Level Measures

We measured two independent variables at the state-level, once again differentiating between income and income inequality. We used ACS 2013-2017 5-year estimates to obtain median household income and the GINI coefficient for each state.

Other independent measures at the state-level we controlled for included percentage of the population who reported being Black, Asian, or Hispanic, and percentage of the population who were male (30, 36). We again used the ACS 2013-2017 5-year estimates for these data.

Statistical Analysis

We compared distributions of the variables between case and control ZIP codes using Students' t-test and by visual inspection of scatter plots. We used multilevel logistic regression models to assess the odds that ZIP code-level or state-level median household income and the GINI coefficient are associated with homicide. Model 1 assessed the association at the ZIP code-level while controlling for ZIP code-level variables, model 2 the state-level while controlling for state-level variables, and model 3 combined both models 1 and 2. Although the matching procedure conditioned upon 6 key ZIP code-level demographic characteristics (proportion Black, proportion Hispanic, proportion Asian, proportion male, proportion aged 15 to 24, and proportion aged 25 to 34), there may be residual confounding by these characteristics (37). We controlled statistically for these 6 characteristics in all 3 models.

We conducted sensitivity analyses comparing the results of the matched case control study to a simple random sample of controls. To maintain comparability between the cases and controls, we set the minimum population size of an eligible control to 25,000. The population of the smallest case ZIP code was 26,500. We set a seed and used the random sample function in R to select our controls.

Results

Descriptive Statistics

Thirty-one of the 35 states in the NVDRS in 2017 were represented in our study (Figure 1). The most case and control ZIP codes came from California (n = 40 and n = 62 respectively). Matched case and control ZIP codes were similar in percent of the population aged 15 to 24, racial demographics, and percent male. They differed, however, in population size and the percent of the population 25 to 34 years old (Table 1). For example, a case ZIP code in New York was matched to a control ZIP code in California. In the case ZIP code, the population consisted of 13% aged 15 to 24, 17% aged 25 to 34, 35% Black, 6% Asian, 52% Hispanic, and 48% male. In the control ZIP code, the population consisted of 17% aged 15 to 24, 15% aged 25 to 34, 12% Black, 10% Asian, 58% Hispanic, and 50% male. In the same matched pair, the population in the case ZIP code was 102,718 compared to 94,327 in the control ZIP code. Results of the case-control matching can be seen in the Appendix.

Table 1
Distribution of ZIP code-level and state-level attributes for matched cases and controls¹

	Cases (n = 250) Mean (SD)		Controls (n = 250) Mean (SD)		P Value
Zip Code Level					
<i>Income</i>					
Median Household Income	46342.39	(11415.10)	63917.91	(19786.93)	<0.0001
<i>Income Inequality</i>					
GINI Coefficient	0.45	(0.04)	0.43	(0.05)	<0.0001
Population size	50197.1	-18438.84	45780.38	(15963.55)	0.0045
<i>Age Group</i>					
% 15 - 24	15.07	(4.95)	14.52	(5.18)	0.2301
% 25 - 34	15.70	(2.77)	14.94	(2.60)	0.0016
<i>Race Ethnicity</i>					
% Black	28.43	(24.71)	25.94	(24.23)	0.2554
% Asian	4.47	(5.40)	4.94	(5.01)	0.3181
% Hispanic	30.26	(26.43)	28.95	(24.66)	0.5685
% Male	48.57	(2.17)	48.62	(1.78)	0.7881
% Unemployed	4.20	(1.28)	3.79	(1.18)	<0.0001
<i>Land Use</i>					
% Land Area that is Retail	2.03	(3.24)	4.82	(6.80)	<0.0001
% Land Area that is Industrial	2.53	(4.57)	13.98	(52.00)	0.0006
% Land Area that is Greenspace	10.75	(14.71)	49.88	(70.82)	<0.0001
Population Density (per km ²)	3424.29	(5440.35)	3400.32	(6592.38)	0.9647
Walk Score	42.31	(29.58)	35.34	(30.78)	0.0101

	Cases (n = 250) Mean (SD)		Controls (n = 250) Mean (SD)		P Value
State Level					
<i>Income</i>					
Median Household Income	60182.41	(9297.23)	65172.5	(8350.00)	<0.0001
<i>Income Inequality</i>					
GINI Coefficient	0.47	(0.02)	0.48	(0.02)	<0.0001
<i>Race Ethnicity</i>					
% Black	13.30	(8.86)	14.82	(8.57)	0.0512
% Asian	6.00	(4.23)	8.13	(4.01)	<0.0001
% Hispanic	18.13	(12.60)	20.64	(12.06)	0.0233
% Male	49.18	(0.57)	49.03	(0.51)	0.0014
* Bolded values are statistically significant at an alpha of 0.05					
¹ Cases and controls were selected from the 35 states participating in the CDC's National Violent Death Reporting System (NVDRS). Case units were defined as the 250 ZIP codes with the highest per capita incidence of violent homicide deaths in 2017. Selected cases had ≥ 5 deaths. ZIP codes eligible for selection as control units (i) had no violent deaths in 2017 and (ii) were located within the 35 NVDRS states. Cases and controls were matched on proportion Black, proportion Hispanic, proportion Asian, proportion male, proportion aged 15 to 24, and proportion aged 25 to 34					

Case ZIP codes were more likely than controls to have lower median household income (\$46,342 vs \$63,918 respectively) and greater income inequality (0.5 vs 0.4 respectively) (Table 1). Case ZIP codes were also more walkable and had lower percentage of land that is retail and industrial and higher percentage of land that is greenspace when compared to the control ZIP codes (Table 1).

Case ZIP codes were in states with lower median household income (\$60,182 vs. \$65,173). Control ZIP codes tended to be in states with higher percentages of Black, Asian, and Hispanic populations (Table 1).

Model Results

In model 1, when controlling for only ZIP code-level variables, a \$10,000 increase in ZIP code-level median household income was associated with an 85% decrease in homicide (OR: 0.15; 95% CI: 0.08, 0.27) (Table 2). When controlling for only state-level variables in model 2, a \$10,000 increase in state-level median

household income was associated with a 46% decrease in homicide (OR: 0.54; 95% CI: 0.38, 0.78). Similarly, a one unit increase in the state-level GINI coefficient was associated with a 46% decrease in homicide (OR: 0.54; 95% CI: 0.36, 0.82 respectively). After controlling for both ZIP code- and state-level variables in model 3, a \$10,000 increase in ZIP code-level median household income was associated with an 83% decrease in homicide and a one unit increase in the state-level GINI coefficient was associated with a 56% decrease in homicide (OR: 0.17; 95% CI: 0.09, 0.31 and OR: 0.44; 95% CI: 0.23, 0.83 respectively). Sensitivity analyses using simple random sample of controls produced similar results and can be seen in the Appendix.

Table 2
Odds ratios and 95% confidence intervals for homicide in matched cases and controls¹

	Model 1		Model 2		Model 3	
	OR	95% CI	OR	95% CI	OR	95% CI
ZIP Code-Level						
Median Household Income	0.15	0.08	0.27		0.17	0.09 0.31
GINI Coefficient	1.03	0.70	1.52		1.35	0.92 1.98
State-Level						
Median Household Income			0.54	0.38	0.78	1.15 0.66 2.02
GINI Coefficient			0.54	0.36	0.82	0.44 0.23 0.83

* Bolded values are statistically significant at an alpha of 0.05

¹ Cases and controls were selected from the 35 states participating in the CDC's National Violent Death Reporting System (NVDRS). Case units were defined as the 250 ZIP codes with the highest per capita incidence of violent homicide deaths in 2017. Selected cases had ≥ 5 deaths. ZIP codes eligible for selection as control units (i) had no violent deaths in 2017 and (ii) were located within the 35 NVDRS states. Cases and controls were matched on proportion Black, proportion Hispanic, proportion Asian, proportion male, proportion aged 15 to 24, and proportion aged 25 to 34. All models controlled for matched variables.

Model 1 adjusted for zip-code level variables

Model 2 adjusted for state-level variables

Model 3 adjusted for all variables

Discussion

This spatial ecological matched case-control study of US ZIP codes identified that income, not income inequality, at the local level is associated with homicide, independent of age, race/ethnicity, and sex. Specifically, lower median household income at the ZIP code-level contributed most substantially to homicide. Income inequality at the state-level, however, was additionally significant when controlling for both ZIP code- and state-level factors.

Our findings advance the collective understanding of violent crime in US neighborhoods with respect to the impacts of socioeconomic disadvantage. Research has identified that income inequality contributes to variation in homicide between neighborhoods, and these neighborhoods tend to have high proportions of racial and ethnic minority residents (31). Black and Hispanic persons in the US are more likely to live in poverty than white persons and more likely to encounter difficulties when improving their economic situations (38). This increased risk has been attributed to economic inequality (11). Previous work has found strong positive associations between income inequality and homicide rates and have suggested that connectedness and community-level collective efficacy are protective factors that may offset many of the negative influences in disadvantaged environment (39, 40). However, results have been inconclusive about the influence of relative and absolute predictors of socioeconomic disadvantage at the local- or state-level. Our findings demonstrate that income at a local level has the greatest impact. This may be accounted for by the differences in how the two variables effect violent crime rates: income inequality, as a measure of *relative* socioeconomic disadvantage, captures the effect of the individual's relationship to larger society, whereas poverty, a measure of *absolute* socioeconomic disadvantage, captures the effect of resource deprivation on individuals. This finding is consistent with theory that suggests at lower levels of aggregation, individual or absolute income will impact health more than income inequality (41). It is only within larger geographic areas that the social heterogeneity which is necessary for the effect of income inequality to occur that one finds a relationship between income inequality and health.

Our results concord with guiding theories of the etiology of violent crime. The routine activities theory holds that crime occurs with the convergence in space and time of motivated offenders, suitable targets, and the absence of capable guardianship (42). Small area variation in population size, composition, and flow will alter the balance of offenders, targets, and guardians in ways that encourage or discourage crime (42). Increased poverty will furthermore increase the presence of motivated offenders, leading to greater crime incidence. Differences in physical conditions, such as poor street lighting, will have similar effects. Further, social disorganization and collective efficacy suggest that formal and informal agents of social control—such as police presence and high social cohesion among neighbors—will deter violent crime due to increased risks that offenders will be detected and punished (7). Several studies have observed that the concentration of potential offenders in neighborhood areas, measured by neighborhood economic socioeconomic disadvantage, is positively associated with crime rates (43, 44). Our findings might further identify that lower income at the ZIP code-level would give rise to an increased presence of motivated offenders. Additionally, guardianship of a place or geographic area is related to the presence of

individuals or systems that can monitor or regulate behavior, whether it is formal (e.g. security guard or police) or informal (e.g. friends or neighbors) (42). For example, higher percentages of retail land area can increase the presence of guardians such as customers, and thus decrease the potential for crime.

This study should be interpreted with its limitations in mind. First, the NVDRS data for 2017 were available from a limited number of states and therefore are not nationally representative. Second, it included only associative analysis and cannot suggest causative mechanisms by which disparities in homicide develop and persist. However, these analyses make several critical contributions. By matching on age, race/ethnicity, and sex and controlling for them in the analysis, we eliminated any potential bias we may have introduced through matching and isolated neighborhood level associations with homicide (37). Additionally, the matched approach yielded a more statistically efficient way to deal with confounding compared to the simple random sample selection of controls.

Conclusions

Multi-level studies of income and income inequality are important to understand the characteristics, independent of race and ethnicity, that contribute to increased homicide rates. Our findings demonstrate that ZIP-code level income and state-level income inequality are associated with high homicide rates in ZIP codes that are otherwise demographically similar. This suggests alleviating low income in local areas and income inequality over larger areas could help reduce homicide rates.

Abbreviations

- **NVDRS:** National Violent Death Reporting System
- **US:** United States
- **ACS:** American Community Survey
- **ZCTA:** ZIP Code Tabulation Areas
- **CDC:** Centers for Disease Control and Prevention

Declarations

Ethics approval and consent to participate

This study was granted approval from the Columbia University Institutional Review Boards.

Consent for publication

All authors have consented for Publication.

Availability of data and materials

Data from the National Violent Death Reporting System can be accessed upon request from the CDC. All other data is publicly available from the Census Bureau and WalkScore's website.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

ANG designed the study, performed the analyses, interpreted the data, and wrote the manuscript. CAM and CNM contributed to the study design and interpretation of the data. CAM, BD, JD, and CNM reviewed and edited the manuscript.

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Figures

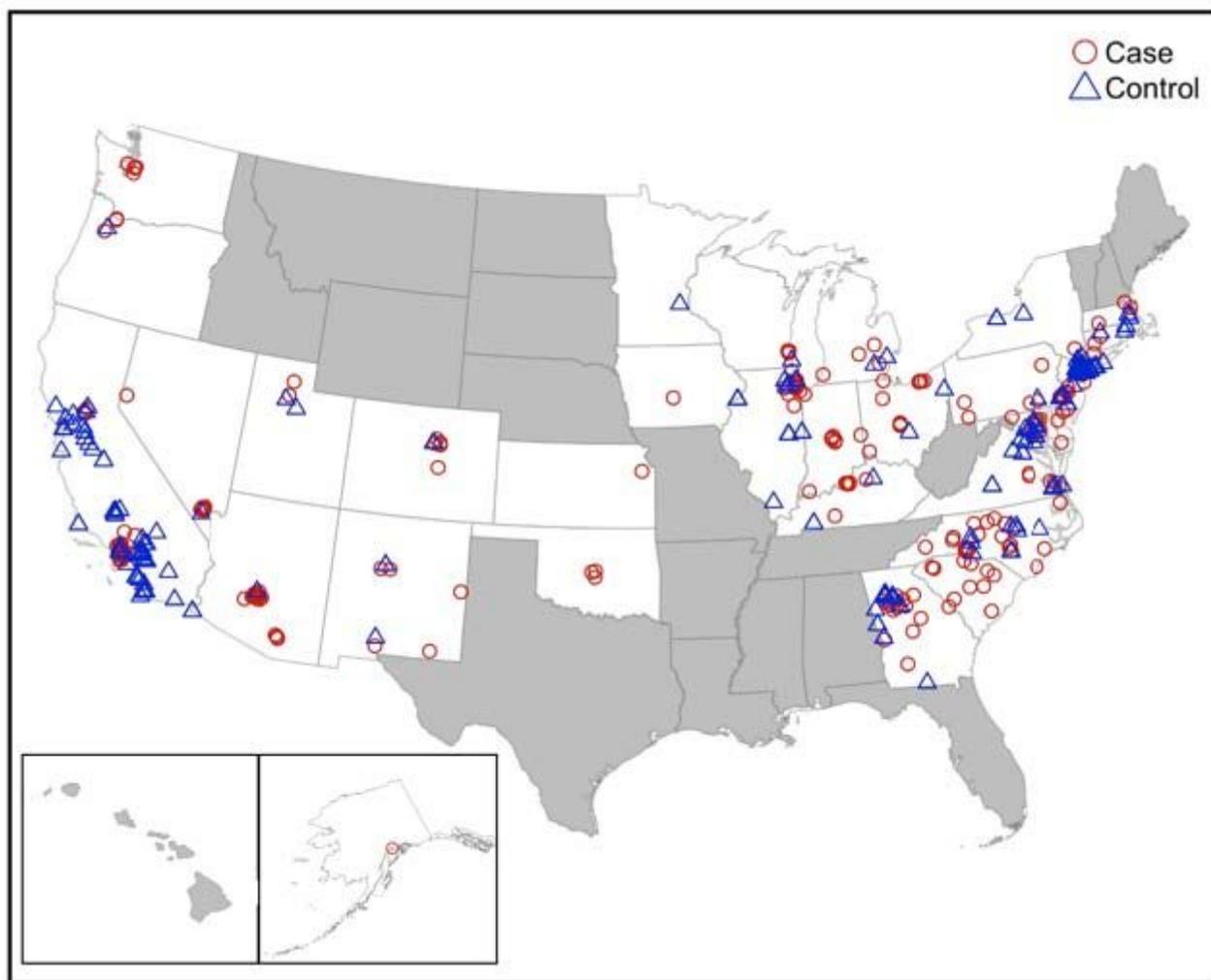


Figure 1

Matched cases and controls from participating NVDRS states in 2017. Cases and controls were selected from the 34 states and four counties in California participating in the CDC's National Violent Death Reporting System (NVDRS). Case units were defined as the 250 ZIP codes with the highest per capita incidence of violent homicide deaths in 2017. Selected cases had ≥ 5 deaths. ZIP codes eligible for selection as control units (i) had no violent deaths in 2017 and (ii) were located within the 34 NVDRS states. Cases and controls were matched on proportion Black, proportion Hispanic, proportion Asian, proportion male, proportion aged 15 to 24, and proportion aged 25 to 34.

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