Social Science & Medicine 280 (2021) 113969

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

# Community-level factors and incidence of gun violence in the United States, 2014–2017

Blair T. Johnson *, Anthony Sisti, Mary Bernstein, Kun Chen, Emily A. Hennessy, Rebecca L. Acabchuk, Michaela Matos

University of Connecticut, USA

A R T I C L E  I N F O

*Keywords:*
Gun violence
Spatial factors
Community health
Social epidemiology
Harm reduction
Laws
Law enforcement

A B S T R A C T

*Rationale and objective:* In the United States, gun violence claims thousands of lives each year and is a pressing public health issue. To gain a better understanding of this phenomenon, this study spatially analyzed county- and state-level predictors of yearly gun violence rates and gun-related casualty rates.

*Methods:* This study modeled hypothesized predictors of gun violence incidence and casualties across four years. Data sources included the Gun Violence Archive (gun violence data in the United States for 2014–2017), the U.S. Census Bureau (socioeconomic, demographic, geologic features), ICPSR (crime reports), the U.S. Geologic Survey (elevation data), and U.S. gun laws and ownership. Random forest analyses identified relevant additional interaction terms to include.

*Results:* The extent to which counties are urban was the most robust predictor of both gun violence incident and casualty rates. Similarly, places characterized by greater income disparity were also more likely to experience higher gun violence rates, especially when high income was paired with high poverty.

*Conclusions:* Community- and state-level features are markedly associated with gun violence. Gun violence is higher in counties with both high median incomes and higher levels of poverty; poverty did not seem related to gun violence rates in counties with relatively low median incomes. Some of these findings may well be due to racial segregation and concentrated disadvantage, due to institutional racism, police-community relations, and related factors.

## 1. Introduction

Gun violence is one of the United States' most pressing public health issues, with upwards of 40,000 deaths per year reported by the U.S. Centers for Disease Control and Prevention (CDC). It is important to gain an understanding of where, and why, gun violence occurs. A gun violence incident is an instance of death, injury, or threat with firearms, regardless of intent. Gun violence casualties consist of injuries or deaths (homicide or suicide) due to firearm use. Spatial and demographic community-level factors, such as income inequality, racial segregation, concentrated disadvantage, household composition, and geographic factors, such as elevation above sea level, are important predictors of a multitude of health outcomes, both internationally and within the U.S. In contrast to existing research on the incidence of gun violence and gun-related casualties, which has typically focused on decades-old, state-level data, the current project modeled county-level data that have been collected relatively recently as well as the restrictiveness of gun laws.

### 1.1. Conceptual background

Numerous studies identify several factors implicated in higher rates of gun violence in the U.S. These factors include high poverty, high-income inequality, low educational attainment, high gun availability and ownership, lenient gun laws (e.g., Geier et al., 2017; Kalesan et al., 2016; Kennedy et al., 1998; Kwon and Cabrera, 2019; Lee et al., 2017; Siegel et al., 2013), racial segregation and concentrated disadvantage, police-community relations and legal cynicism (Kirk and Papachristos, 2011; Sampson and Bartusch, 1998). Yet, these studies focus either on trends at the state level or on neighborhood comparisons within one to three cities (for reviews see Braga et al., 2018; Butts et al., 2015) and have not made systematic comparison across communities nationally. We have found only one study that compared different types of gun

* Corresponding author. Department of Psychological Sciences, Institute for Collaboration on Health, Intervention, and Policy (InCHIP), University of Connecticut, 2006 Hillside Road, Unit 1248, Storrs, CT 06269-1248, USA.
*E-mail address:* blair.t.johnson@uconn.edu (B.T. Johnson).

https://doi.org/10.1016/j.socscimed.2021.113969
Received in revised form 23 April 2021; Accepted 25 April 2021
Available online 10 May 2021

violence; it found parallel trends between mass shootings, homicides, and suicides (Kwon and Cabrera, 2019). It is worth noting that many varieties of gun violence are predictable from the same variables; thus, communities that experience one form of gun violence are likely to experience the other forms, but, to date, no study has provided direct evidence for this observation.

Higher rates of gun violence in the U.S. are linked to the easy availability of guns, high levels of gun ownership, and lenient gun laws. Within the U.S., high rates of gun violence are also linked to racial segregation and concentrated disadvantage, especially high poverty, high-income inequality, and low educational attainment (Massey, 1995). African Americans are more likely than both White and Latinx people to "reside in ecologically distinct environments of concentrated disadvantage" (Sampson and Bartusch, 1998, p. 798). Such segregation is the legacy of systemic racism in the U.S. resulting from the history of enslavement, Jim Crow segregation, and redlining as well as racist crime control policies that have resulted in the mass incarceration of racial minorities, all of which have devastated communities of color (Alexander, 2020; Garland, 2001; Hinton, 2016). Neoliberal economic policies have been particularly devastating financially to racially segregated minority communities (Wacquant, 2009).

Current and historical police practices directly influence levels of gun violence in racial minority communities. Such communities experience surveillance and harassment by police for petty violations or no reason at all and the police fail to serve those communities when they ask for assistance and protection from serious crime, which leads to mistrust of police in minority communities (Desmond and Valdez, 2013; Rios, 2011). Research has shown that African Americans in minority communities have less tolerance of deviance and violence than European Americans (Sampson and Bartusch, 1998) but greater levels of legal cynicism, "a cultural frame in which people perceive the law as illegitimate, unresponsive, and ill-equipped to ensure public safety" (Kirk and Papachristos, 2011, p. 1190). High levels of legal cynicism in these segregated communities of concentrated poverty and lack of educational and economic opportunities can contribute to higher levels of gun violence as citizens are left to resolve disputes on their own and to protect themselves (Anderson, 2000; Kirk and Papachristos, 2011). Gun violence coupled with racist policing (past or present) harms the collective efficacy of communities and their ability to combat violence because police are viewed as threats to the safety of community members, rather than as resources (Carter et al., 2017; Sierra-Arevalo et al., 2016; Sunshine and Tyler, 2003). Overpolicing such as invasive police encounters or stop-question-and-frisk policies disproportionately target racial minorities, especially African Americans, and have a detrimental impact on racial minority communities in terms of mental and physical health and other forms of well-being, which are felt regardless of whether they themselves have been stopped by police (Jackson et al., 2019; Menakem, 2017; Sewell and Jefferson, 2016; Sewell et al., 2016; Turney, 2020). Thus, it is quite likely that neighborhood variations in police-community relations may help to explain varying levels of gun violence across similarly situated communities. As Abt (2019) summarizes, "No one kind of deprivation is responsible [for gun violence in urban areas]; instead, it is multiple deprivations, all operating at the same time, all fixed on the same people living in the same place, that eventually result in high levels of victimization and crime…It is impossible to examine concentrated urban poverty without acknowledging America's shameful legacy of racial segregation." This history of systemic racism in the U.S. has a variety of negative health consequences as well, such as high levels of psychosocial stress, that have been linked to biological inflammation and premature aging (e.g., (Simons et al., 2016), heightened infant mortality (Orchard and Price, 2017), and shorter lifespans (Leitner et al., 2016).

Relative deprivation theory (Merton, 1938; Runciman, 1966) might suggest that higher income inequality will result in higher levels of gun violence and there is some support for this assertion concerning mass shootings. Specifically, Cabrera and Kwon (2018) showed that income inequality was more predictive of mass shootings in the U.S. to the extent that county-level income levels were higher; they later posited that areas of high inequality may "foster an environment of anger and resentment that ultimately leads to mass shootings" (p. 139). This position aligns closely with Pickett and Wilkinson's (Pickett and Wilkinson, 2015; Wilkinson and Pickett, 2011) theory about the causal effects of income inequality. There have been many demonstrations of the deleterious health effects of higher income inequality. These studies are focused on the richest nations in the world, often accompanied with analyses of states within the single richest nation in the world, the U.S. (Pickett and Wilkinson, 2015). Greater income inequality thus logically matters more when counties have higher median income than when they have lower income, a hypothesis we tested directly. In counties with higher proportions of minority people and higher median income, this pattern may reflect racial segregation, a legacy of enslavement, Jim Crow segregation, and redlining (Wong et al., 2020).

Importantly, scholars have noted the likelihood that acts of violence in an area are likely to increase the odds of further violence (Fagan et al., 2007); spreading through and concentrating in social networks (Papachristos et al., 2015). In urban areas, only a very small number of people are responsible for the majority of community gun violence (Abt, 2019; Kennedy, 2011). Hence, scholars increasingly think of gun violence as a public health problem that is transmitted through specific, concentrated networks. Similarly, other research focused on counties in California found large variability in firearm mortalities over space (Pear et al., 2018), suggesting that gun violence is concentrated in spatially identifiable networks. Other studies compare gun violence across neighborhoods within cities (Braga et al., 2018; Butts et al., 2015). In contrast, we compare these trends across all counties in the U.S., instead of states or census regions, though future research may benefit by looking at an even more finely tuned level of the neighborhood.

Finally, populations in higher elevations have notably increased levels of suicide rates, and one likely cause is altitude-related-hypoxia, a factor that stresses the body. It seems likely that elevation is also connected with greater chances of gun violence (Brenner et al., 2011; Kim et al., 2011), although other research suggests that more extreme elevations are necessary to detect such effects (Kious et al., 2018). Controlling for this factor helps to ensure that the foregoing factors have unique effects that are not due to differing elevation levels.

Thus, there is a great deal of research suggesting that community- and structural-level factors are connected to gun violence, which corresponds with research on other health phenomena (Leitner et al., 2016; Pickett and Wilkinson, 2015). Yet, as Siegel et al. (2013) concluded, this research generally relies on decades-old databases and has not examined temporal changes in gun violence, even though gun ownership per capita has decreased in recent decades up to the COVID-19 pandemic.

### 1.2. Study aims, research questions, and hypotheses

To date, few gun violence studies have examined structural- and community-level factors at the county level across the U.S. Analyses of relatively recent data remain rare, and no county-level study has compared moderators of gun violence and casualties over time. Thus, our primary aim is to understand what community-level factors have been strongly linked to gun violence in the U.S. and whether they hold predictive value so that future work can directly address these factors to reduce gun violence overall. Although scholars have examined the relationship between gun violence and firearm availability and ownership (Geier et al., 2017; Kalesan et al., 2016; Lee et al., 2017), there is theoretical support for examining additional community-level characteristics to ascertain which factors, in interaction, are associated with either increased or decreased gun violence in certain geographic areas. Based on the conceptual background in the preceding section, we hypothesize that concentrated disadvantage, especially in racial minority communities, is related to higher levels of gun violence. Because African Americans are more likely to reside in areas of concentrated disadvantage, the legacy of systemic racism, we hypothesize that income inequality, poverty, proportions of racial minorities (linked to the stains of systemic racism), lower marriage rates, lack of education, and higher crime levels are related to increased gun violence rates, along with elevation. We also had an *a priori* interaction hypothesis such that gun violence is more likely in communities with higher income inequality, but especially when these communities have higher median income.

We had no reason to expect that models would not replicate year to year; thus, we expected that predictors will show similar relationships to gun violence and gun-related casualties over time. We examine not only gun violence incident rates but also gun-related casualty rates to determine whether factors predictive of one are predictive of both. Because our analysis is focused on county-level incidence of gun violence and casualties across four years of data, we could identify outliers, that is, communities and states that consistently perform better or worse than the structural- and community-level factors predict. Finally, because we also invoked random forest models, we were able to identify whether novel interactions of important community characteristics were omitted from models (or that improved on *a priori* predictions).

## 2. Methods

To address these aims and examine our hypotheses, we collected data from existing sources and used multiple methods of confirmatory and exploratory analysis. Before initiating the analyses, we registered a protocol on the Open Science Framework (https://osf.io/f8j9n/?view_only=ed307a0c1c4a445e893b14bcedd93585); it included our aims, hypotheses, and planned analyses.

### 2.1. Gun violence incidence and casualties

Data related to gun violence incidence in the U.S. are taken from the Gun Violence Archive (GVA), a non-partisan, not-for-profit corporation whose mission is "to document incidents of gun violence and gun crime nationally to provide independent, verified data to those who need to use it in their research, advocacy or writing" (GVA, 30 July 2019). The GVA collects these data daily from over 7500 commercial, government, law enforcement, and media sources. To validate their counts, we used the GVA's counts of fatalities from 2017 at the state level and correlated these with CDC figures for the same year. We expected that the GVA would undercount casualties because it is less sensitive to gun-related suicides (which media reports routinely ignore), but, because we expected that the counts will nonetheless be highly correlated with the CDC's counts, we did not anticipate that undercounts would invalidate the models evaluated.

In our main analyses, the outcome variables are the aggregated yearly counts of recorded firearm incidence within each county, along with gun-related casualties. These values were taken between January 1st, 2014 and December 31st, 2017, creating totals for each outcome variable in each year; the version available on March 31st, 2018 was utilized. Although the GVA recorded some gun-related violence in 2013, we omitted it because this year only had partial measures of gun incidents. Because the GVA data omitted the large Las Vegas mass shooting from November 2017, these tallies were entered manually into the database. To control for differences in population between each county, we analyzed gun violence and casualties as rates per 10,000 county residents. Geocodio (Dotsquare, 2018), an online geocoding program, was used to obtain county FIPS codes for each reported incident so that they could be matched to the appropriate county-level features. For each county, we computed yearly incident counts, casualty counts, as well as their rates per 10,000 residents.

### 2.2. Socioeconomic, demographic, and geological features

Socioeconomic and demographic data were obtained at the county level from the U.S. Census Bureau and the Inter-University Consortium for Political and Social Research (ICPSR). The U.S. Census offers its 2016 5-year estimates for *income inequality* (i.e., Gini coefficient); *median income* (median household income in the past 12 months); *poverty* (proportion of individuals living below the poverty line); *college graduates* (proportion of residents having a bachelor's degree aged 25 years and older); *marital status* (proportion of population 15 years and older: married, except separated); *urbanness* (proportion of county residents living in an area defined as urban by the Census Bureau); *minority* (proportion of racial minorities other than Whites); and *population size* (total number of people). The ICPSR archived Universal Crime Reports in both 2014 and 2016 on *crime totals* (total number of violent or property crimes, that occurred within each county); this value was divided by total population to create a crime rate. (Note that gun crimes are not subtracted from this index; hence its association with gun violence is over-estimated.) We used the 2014 rate in the 2014 and 2015 analyses and the 2016 rate in the 2016 and 2017 analyses.

*Elevation* (average value of elevation from a set of survey observations within a county in kilometers) was taken from the U.S. Geologic Survey. The number of observations within a county during this survey ranged from 1 to 1962; the mean of these observations was taken to create one value for each county. Elevation data were available for 99.6% of the counties (the 12 missing counties had FIPS county codes 02158, 02275, 17039, 17151, 29053, 29055, 29059, 29065, 29067, 29071, 46102, 51595 and had populations ranging from 2401 to 102063; these cases amount to only 0.07% of the U.S. population).

Variables measured at the state-level included the strictness of *gun laws,* the 2014 index created by the Brady Campaign (2015) and *number of guns owned,* the 2014 proportion of state households that own guns, as gauged by Kalesan et al.'s (2016) representative U.S. survey.

### 2.3. Zero-inflated Poisson generalized linear mixed-effects models

We analyzed aggregated counts within each county for each of the four years between 2014 and 2017 to assess gun violence incidence and gun-related casualties. Our preregistration plan specified to conduct principal component analysis for any variables that were correlated greater than 0.80 in magnitude, but none reached this criterion: Median income and proportion of the population living below the poverty line were the most strongly correlated ($r = -0.75$).

We used zero-inflated Poisson generalized linear mixed-effects models (GLMM) with canonical link (logarithm) for the primary analyses. The zero inflation was evident, as across all years in the analysis, 31% of counties had tallies of zero gun violence incidence and 39% had no gun-related casualties. The model offset counts of gun violence and gun-related casualties by the population size of the county divided by 10,000. Thus, incidence and casualties were analyzed as a yearly rate per 10,000 county residents. County-level random effects were included to account for both potential spatial correlations and individual effects among counties (Banerjee et al., 2014). Specifically, the county-level random effect consists of two components: a structured spatial component (conditional autoregressive structure of order 1) to account for similarities induced by spatial adjacency, and an unstructured independent and identically distributed component to account for additional individual effects (Bakka et al., 2018; Besag, 1974; Besag et al., 1991). In the specification of spatial adjacency, a county was determined to be neighboring another if it shared any part of a common border with another. State-level random effects were also included to account for unexplained variations between states in the outcome variable; this random effect component was assumed to be independent and identically distributed from state to state. These effect estimates allowed us to check how each state performed relative to what the model predicted based on the county-level predictors and effects. We used the R-INLA package (www.r-inla.org) to perform Bayesian inference, with default flat prior settings (Blangiardo et al., 2013; Rue et al., 2009). R-INLA is designed for fitting a wide range of latent Gaussian models including generalized linear mixed and spatial models; it uses the Integrated Laplace Approximation (INLA) as a computationally efficient alternative to MCMC for Bayesian inference (Lindgren and Rue, 2015). Before implementing the model, the predictor variables were standardized. Initial models included latitude and longitude as predictors, but, as latitude and longitude are highly confounded with county-level predictors, these models were unstable; thus, these were omitted from the final models. Posterior means are used as the point estimates of the parameters. The team adopted a more stringent criterion for statistical significance: a parameter is significant if its 99.5% credibility interval does not include zero.

As there are many potential interaction terms, we took a machine learning approach to identify any potentially important ones. Specifically, to evaluate the importance of each two-way interaction, we fitted a random forest model (in the R statistical environment using the package 'randomForest', version 4.6–14) of the response with the interaction term and all the predictors (using 1000 trees and the default number of random starts). The importance of the interaction term was computed based on how much it contributes to decreasing the impurity of the trees measured by the residual sum of squares.

The results for each interaction term were then compared. This process identified an interaction that our pre-analysis plan did not identify between income and poverty (although this one is a more extreme form of the hypothesis we had made between income and income inequality). It also identified two that did not reach significance in any of the years modeled: (1) between urbanicity and gun law restrictiveness and (2) between income inequality and proportion of minorities (results not shown).

## 3. Results

### 3.1. State-level comparison of gun violence data and descriptive statistics for modeled variables

As expected, the GVA under-reported gun-related deaths when compared to CDC totals each year (Table 1; Table S1 provides a more nuanced breakdown of the incidence levels). Nonetheless, the correlation between GVA gun-related death totals and CDC gun-related death totals at the state-level is quite high (Table 1; see Fig. S1 in the online supplement). GVA counts of gun violence deaths and of suicides *were* correlated with CDC gun deaths at values above 0.95: These statistics strongly support the validity of the GVA for predictive modeling (though not for the extent of gun violence, as suicides are very likely to be underreported and thus underrepresented in the GVA data).

Table 2 presents descriptive statistics for variables included in the analysis. These untransformed values show that the counties included in the analyses vary widely on these dimensions. Table 3 presents the correlations among these variables. Of note, the matrix for outcomes shows that incidence of gun violence is highly correlated with casualties and that counties with higher gun violence in one year were likely to experience it in other studied years; hence, gun violence levels are fairly stable over time.

**Table 2**
Descriptive statistics of predictor variables (before standardization) as well as the criterion variables.

| Factor | Mean | *SD* | Range | *N* counties |
|---|---|---|---|---|
| Income inequality | 0.444 | 0.035 | 0.321, 0.620 | 3142 |
| Median annual income | 48,005 | 12,608 | 18,972, 125,627 | 3142 |
| Proportion below poverty line | 0.154 | 0.063 | 0.030, 0.567 | 3142 |
| Proportion college graduates | 0.212 | 0.093 | 0.047, 0.781 | 3141 |
| Proportion married | 0.516 | 0.070 | 0.199, 0.738 | 3142 |
| Proportion urban (population at least 100,000) | 0.414 | 0.315 | 0.000, 1.000 | 3142 |
| Proportion minority population | 0.166 | 0.166 | 0.000, 0.909 | 3142 |
| Gun law restrictiveness | 18.900 | 26.300 | −8.000, 75.000 | 3142 |
| Crime rate | 0.032 | 0.019 | 0.000, 0.210 | 3177 |
| Proportion households owning guns (2014) | 0.333 | 0.138 | 0.052, 0.617 | 3142 |
| Elevation (in kilometers) | 0.397 | 0.451 | 0.000, 3.020 | 3130 |
| 2014 Gun violence incidence (per 10,000) | 0.985 | 1.580 | 0.000, 23.202 | 3136 |
| 2014 Gun violence casualties (per 10,000) | 0.675 | 1.422 | 0.000, 46.404 | 3136 |
| 2015 Gun violence incidence (per 10,000) | 1.099 | 1.734 | 0.000, 20.932 | 3136 |
| 2015 Gun violence casualties (per 10,000) | 0.791 | 1.306 | 0.000, 20.743 | 3136 |
| 2016 Gun violence incidence (per 10,000) | 1.188 | 1.810 | 0.000, 21.500 | 3136 |
| 2016 Gun violence casualties (per 10,000) | 0.855 | 1.588 | 0.000, 36.675 | 3136 |
| 2017 Gun violence incidence (per 10,000) | 1.254 | 1.756 | 0.000, 20.873 | 3136 |
| 2017 Gun violence casualties (per 10,000) | 0.859 | 1.430 | 0.000, 16.680 | 3136 |

*Note.* Higher values imply more of the factor in question.

### 3.2. County-level distribution of gun violence incidence and casualties

Fig. 1 shows how gun violence incidence is distributed spatially (see supplementary materials for casualties). Each year, the GVA recorded an increasing number of occurrences of both response variables, which is visible through the increasingly darker shading patterns seen in the maps between 2014 and 2017 (see also Table 2 for mean levels). The differences between the yearly spatial distributions of these rates demonstrate that gun violence incidence and gun-related casualties are not necessarily occurring in the same places with the same intensity. Thus, there is considerable variability across counties in terms both of gun-violence incidence and of casualties.

### 3.3. Zero-inflated Poisson generalized linear mixed-effects models

Because the modeled results for the two outcomes (incidence and casualties) were so parallel, here we report the results for only one, gun violence incidence, which also had greater variability and which is more

**Table 1**
State-level comparison of Gun Violence Archive (GVA) counts with the Center for Disease Control and Prevention's (CDC) counts of deaths due to firearms, 2017.

| Counts | *M* (*SD*) | GVA counts | | | | |
|---|---|---|---|---|---|---|
| | | Incidence | Casualties | Deaths | Injured | Suicides |
| **GVA counts** | | | | | | |
| Incidence | 1203.73 (1134.12) | – | | | | |
| Casualties | 906.06 (957.28) | 0.9744 | – | | | |
| Deaths | 304.08 (317.88) | 0.9240 | 0.9439 | – | | |
| Injured | 601.98 (665.50) | 0.9602 | 0.9875 | 0.8800 | – | |
| Suicides | 284.53 (290.77) | 0.9311 | 0.9500 | 0.9995 | 0.8891 | – |
| **CDC deaths** | 793.46 (762.46) | 0.8417 | 0.8512 | 0.9579 | 0.7670 | 0.9538 |

*Note.* Statistics include the District of Columbia except for the CDC counts; $N = 51$ for GVA and $N = 50$ for CDC. All correlations are statistically significant, *p-value* $<.005$.

**Table 3**
Correlations between predictor variables (A) and between outcome variables over time (B: gun violence incidence and all casualties).

| Group and variable | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **A: Predictor variables** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** |
| 1. Income inequality | – | | | | | | | | | | |
| 2. Median annual income | −0.37 | – | | | | | | | | | |
| 3. Proportion below poverty line | 0.52 | −0.75 | – | | | | | | | | |
| 4. Proportion college graduates | 0.05 | 0.69 | −0.48 | – | | | | | | | |
| 5. Proportion married | −0.48 | 0.35 | −0.61 | 0.02 | – | | | | | | |
| 6. Proportion urban (population at least 100000) | 0.11 | 0.36 | −0.16 | 0.50 | −0.31 | – | | | | | |
| 7. Proportion minority population | 0.37 | −0.15 | 0.50 | −0.01 | −0.67 | 0.20 | – | | | | |
| 8. Gun law restrictiveness (in 2014) | −0.05 | 0.34 | −0.23 | 0.26 | −0.07 | 0.25 | −0.03 | – | | | |
| 9. Crime rate | 0.19 | −0.16 | 0.18 | −0.04 | −0.26 | 0.24 | 0.15 | −0.09 | – | | |
| 10. Proportion households owning guns (in 2014) | 0.10 | −0.21 | 0.22 | −0.19 | −0.02 | −0.17 | 0.12 | −0.57 | 0.12 | – | |
| 11. Elevation (in kilometers) | −0.13 | 0.04 | −0.13 | 0.12 | 0.23 | −0.09 | −0.24 | −0.11 | 0.04 | 0.22 | – |
| **B: Outcome variables** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | | | |
| 1. Gun violence incidence 2014 | – | | | | | | | | | | |
| 2. Gun violence incidence 2015 | 0.56 | – | | | | | | | | | |
| 3. Gun violence incidence 2016 | 0.54 | 0.63 | – | | | | | | | | |
| 4. Gun violence incidence 2017 | 0.52 | 0.54 | 0.61 | – | | | | | | | |
| 5. Gun casualties 2014 | **0.81** | 0.37 | 0.36 | 0.35 | – | | | | | | |
| 6. Gun casualties 2015 | 0.59 | **0.76** | 0.48 | 0.47 | 0.41 | – | | | | | |
| 7. Gun casualties 2016 | 0.50 | 0.46 | **0.79** | 0.46 | 0.35 | 0.48 | – | | | | |
| 8. Gun casualties 2017 | 0.47 | 0.43 | 0.46 | **0.79** | 0.38 | 0.50 | 0.44 | – | | | |

*Note.* Predictor variables do not vary over time; within the outcome variables, **boldface** correlations highlight that, for each year, incidence and casualties correlate markedly.

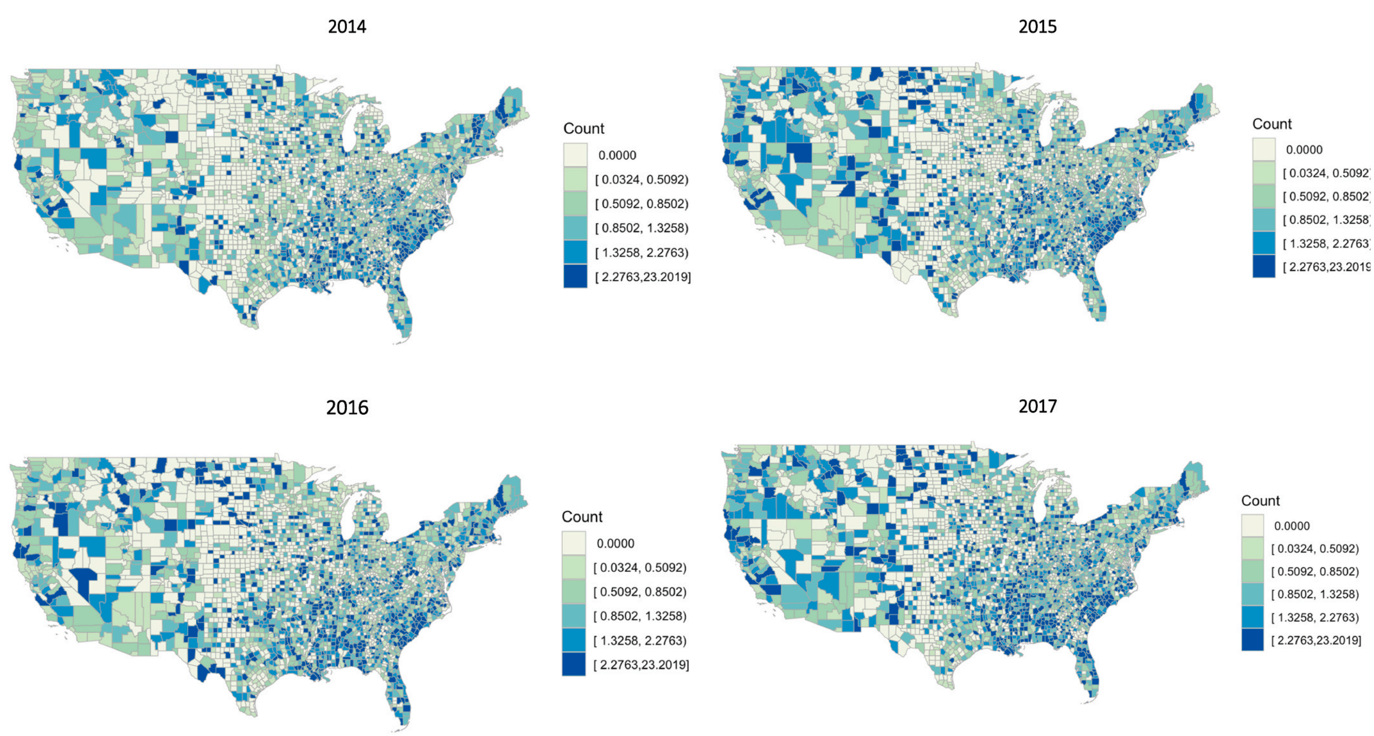


**Fig. 1.** County-level gun violence in the continental U.S., 2014–2017 (shown as rates per 10,000 population); Hawai'i and Alaska are not shown.

favorable for modeling. (The online supplements offer the other results.) Median income, degree urban, share of population minority, and crime rates were the most robustly associated with gun violence: For each year, gun violence was higher when median income was lower, the county was more urban, had more minorities, and higher crime rates. Yet, when taking into account the interaction between poverty and median income, higher median incomes along with greater levels of poverty (which are reflective of residential patterns in racially segregated counties) increase gun violence. Greater income inequality was associated with more gun violence in 2016 and 2017 (but not 2014 and 2015), although its association was quite uniform across years. Gun law restrictiveness was related to decreased gun violence in 2014 (and in 2015, in the model that included the interaction), but not in 2016 or 2017. Rates of gun ownership were unrelated to gun violence in all four years, as was proportion of college graduates, proportion below the poverty line (as a main effect), gun ownership rates, and elevation.

Three interactions were implied by the CART analysis, but only one reached significance in the spatial analyses. Fig. 2 shows the remaining significant interaction for median income and poverty, which exhibited a pattern very similar to that predicted for median income and income inequality: While a higher proportion of residents living in poverty was not itself a direct predictor of increased gun violence, the combined increase of poverty level and higher median income in a county had the strongest impact on increasing the gun violence incidence rate of the interaction terms and their component variables. Fig. 3 displays county-level residual values for each year of the analysis; these indicate where the models under- and over-perform in each year.

### 3.4. State performance

Each year of analysis provides an opportunity to assess how states performed relative to what the model predicted using all factors of their counties. To visualize the results, we plot the estimated state-level effect values in descending order with their 95% credibility intervals in Fig. 4 for the year 2017; the majority of state-level effects remain stable across the studied years. Alaska consistently performed worse, having more gun violence than the factors predicted they should have. In contrast, Hawaii consistently performed better, having less gun violence than the factors predicted (see supplemental materials for analyses in other years).

## 4. Discussion

This study modeled gun violence in the U.S. over the years 2014 through 2017, accounting for county-level spatial correlation. Modeling gun violence at the county level is more focused than many prior studies have done. Moreover, the study incorporated new predictors and interactions that past research has not examined. Overall, the most robust predictor of both gun violence incidence rates and gun-related casualties was the degree to which the county was urban (Tables 3 and 4). Thus, holding all else constant, counties with larger urban centers had higher rates of gun violence. Higher median income was also consistently significantly related to reduced rates of gun violence incidence and gun-related casualties across all four years, but this factor interacted with poverty. Specifically, we predicted that income and income inequality would interact, such that where income is highest, income equality will matter most; this prediction was supported in analyses, albeit in a more precise fashion than we expected. Indeed, counties that had high median incomes combined with higher levels of poverty were associated with more gun violence, whereas poverty did not seem to affect gun violence rates in counties with relatively low median incomes (Fig. 2). The presence of high poverty rates even in communities with overall high median incomes would seem a veritable definition of income inequality. It also suggests racial segregation and concentrated disadvantage within those counties, many of which include mixes of impoverished urban areas and wealthy suburbs. These findings suggest that it is not the presence of racial minorities per se that affects gun violence rates, but that higher income inequality in counties with higher proportions of racial minorities leads to higher levels of gun violence. This pattern (1) may well reflect the historical factors that include racial targeting by police and segregation in housing patterns in the U.S., the legacy of institutional racism (e.g., Massey, 1995; Wong et al., 2020); it also (2) likely reflects police relationships, historical patterns in these areas of police targeting minorities, factors that lead minorities to mistrust police. Higher marriage rates were associated with less gun violence in two of the studied years (and had similar coefficients in the other years). Marriage may significantly reduce gun violence because married couples are less likely to be in poverty than single people (Theide et al., 2017); yet, the meaning of this finding should be interpreted with caution because those who are poor are less likely to marry and poverty itself is a stressor on marriage (Heath, 2020); furthermore, racial minorities face job discrimination and structural disadvantage in the labor market suggesting that the relationship between economic security and marriage may be more tenuous for racial minorities (Theide, Kim, and Slack, 2017). Models also determined that gun law restrictiveness was significantly associated with less gun violence in 2014 and 2015; this pattern abated over time, perhaps because states altered gun laws after 2014 or because enforcement of restrictive gun laws declined over time. Future research should investigate such possibilities.

Finally, we hypothesized that elevation would be associated with higher levels of gun violence, as prior work has shown suicides to be more likely at higher altitudes (Brenner et al., 2011; Kim et al., 2011). Our results showed no linkage between elevation and gun violence. Because gun violence counts obscured suicides, the pattern might emerge if suicides were investigated specifically.

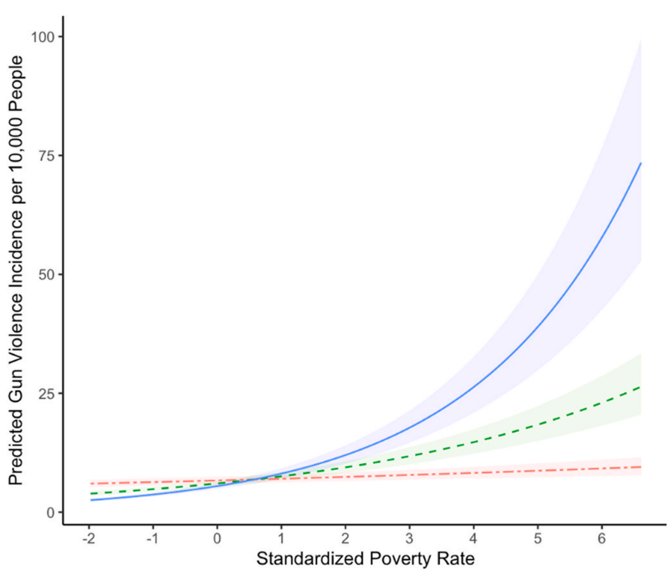


**Fig. 2.** Gun violence in the year 2017 as a function of two interacting variables (see Table 4 for model details). In counties with higher median incomes, there was more gun violence to the extent that there were more people living beneath the poverty line (especially blue, solid line, but also green, dashed line); in counties with lower median incomes (red, dash-dot line), poverty levels were not associated with gun violence. These patterns parallel those found in 2014–2016 (see online supplements).

### 4.1. Strengths, limitations, and future directions

This study is the first of its kind to use multilevel modeling with random effect components to analyze the spatial distribution of gun violence and gun-related casualties over time. Previous studies examined only single years or subsets of firearm violence. Nonetheless, this study faced several limitations. The database used to conduct the analysis only contained gun violence counts from a four-year period (2014–2017), and these counts underrepresented what actually occurred, based on CDC records (see Table 1 and Fig. S1); still, over time the GVA accounts more closely aligned with CDC records. Thus, it is difficult to analyze long term trends or the impact that any newly implemented gun law policy has made over time. It is only possible to draw clear conclusions about this recent four-year window. Yet, due to the underrepresentation of incidence found in the GVA database, the restriction of range in counts implies that the actual model coefficients, especially for gun casualties, are in reality larger than what was found in this study (see Bland and Altman, 2011). Suicides by guns are typically much more lethal than other methods of attempting suicide. Although suicides account for two-thirds of U.S. gun deaths, that number is likely masked by our measure of gun violence, as these include any incident of death, injury, or threat with firearms. Thus, our analysis may miss particular suicide types such as white male suicides of despair (e.g., Abrutyn and Mueller, 2018). Four years of data might permit inferences of plausible causality (e.g., through the use of temporal lags), but the community-level predictors were not available at a yearly level to allow for this analysis. Most predictor variables are five-year estimates from the Census Bureau's American survey. In addition, interesting community characteristics such as divorce rates, gentrification rates, and

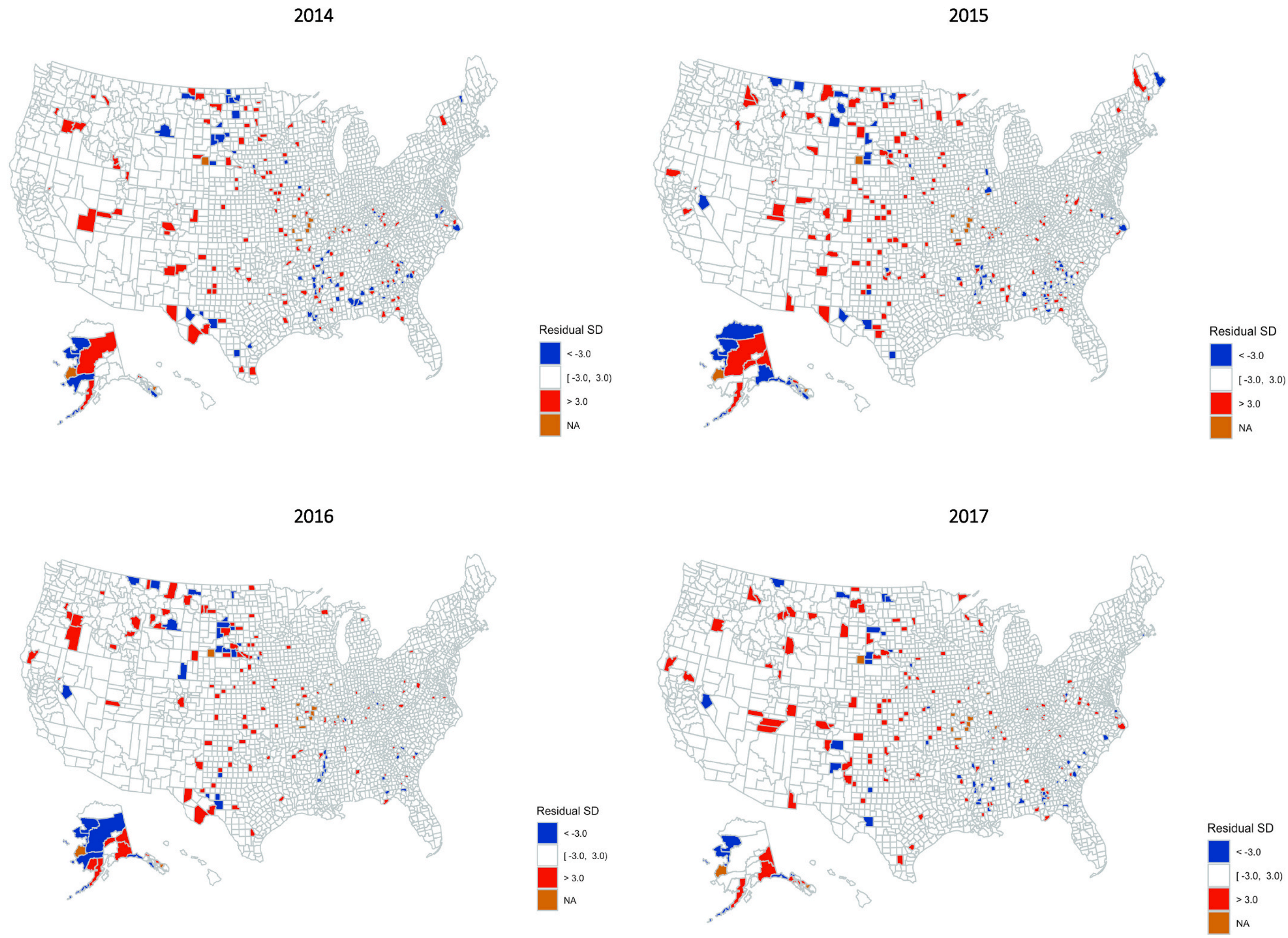


**Fig. 3.** County-level residuals from zero-inflated Poisson GLMM models for the incidence of gun-related violence for each year analyzed (Table 4). Values in blue are extreme in terms of having less gun violence than expected based on models; those in red have more gun violence than expected; those in white are relatively close estimates.

weather patterns were difficult to obtain for each county and would have widely shrunk the scope of the analysis; yet, we anticipate that these factors might not vary substantially across years. We were forced to assess gun law restrictiveness and gun ownership at the state-level (because this information was not available at the county level). Our study also does not take into account the implementation of gun laws since 2014.

Our study does not directly take into account other potentially important historical and systemic factors, such as residential segregation, though taken together, our findings about poverty, median income, income inequality, and proportion of racial minorities, reflect the history of systemic racism in the U.S. that has resulted in the structural isolation, concentrated poverty, and lack of economic and educational opportunities for Black and Brown people. Furthermore, the history of police practices such as stop-question-and-frisk or the implementation of policies such as "three strikes" that are disproportionately used against racial minorities (Sewell and Jefferson, 2016) and the lack of attention that police give to violent crime in racial minority communities (Abt, 2019), leads to racial trauma and legal cynicism. All of these factors likely lead to higher levels of gun violence. Thus, our findings about county-level predictors are consistent with previous studies of gun violence at the neighborhood level within a few select cities as well as with the qualitative literature (e.g., Anderson, 2000). Direct measures of historical and systemic factors such as residential segregation would be beneficial to include in future research, as would gun ownership rates separated for minorities and Whites. In response to an anonymous reviewer, we examined a commonly used index of racial segregation from the 2010 census, dissimilarity, as an additional predictor of gun violence, one for White-Black racial groupings and one for White-Latinx; values of this index assess the degree to which the proportions of minority and majority group members within individual areas are similar to the proportions defined by area boundaries. Higher values imply more racial dissimilarity in residential housing patterns. Analyses showed that more racial segregation between White and Latinx groups did not predict gun violence incidence significantly over and above the predictors in Table 4; yet, in three of the years (2014, 2015, and 2017) the White-Black dissimilarity index *did* significantly predict gun violence incidence, such that more gun violence occurred in areas with more Black-White residential racial segregation. The fact that racial residential segregation predicts some gun violence over and above the predictors in our study suggests that racial segregation deserves greater attention in future studies of gun violence. This finding is consistent with and supports our interpretation of our findings, namely, that counties with higher median income, higher levels of poverty, and higher percentages of racial minorities have the highest gun violence rates because of the legacy of systemic racial inequality reflected in segregated housing patterns and associated disadvantage at the county level.

The technology and ability to track gun violence incidence improve each year. In the future, gun violence incidence will likely be reported with better accuracy. Also, with that will come additional years of data,

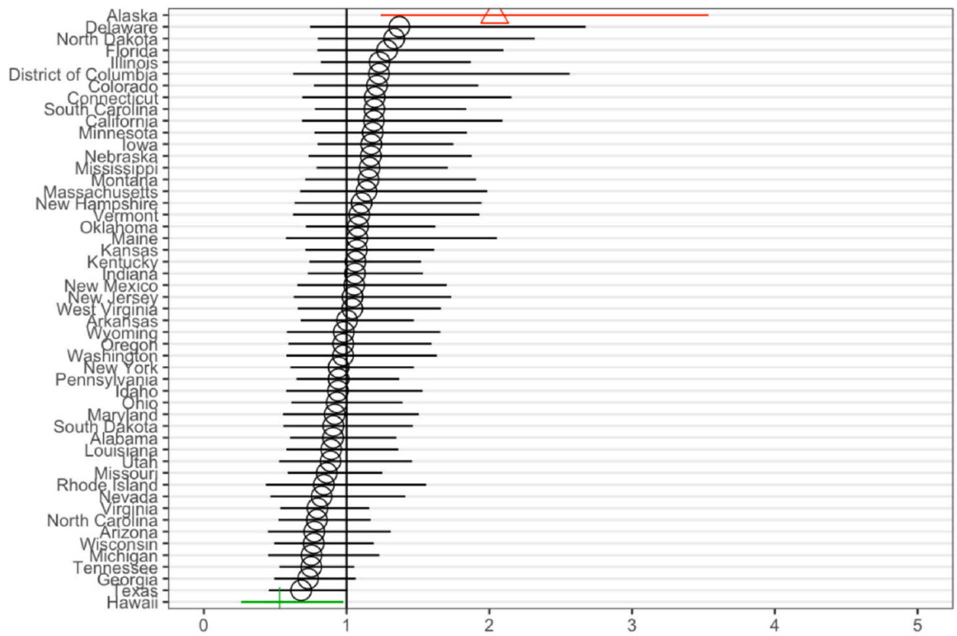


**Fig. 4.** State-level effects, implying performance relative to predictions of the model predicted (Table 4), plotted in descending order for the most recent year in the analysis, 2017. Red indicates values significantly greater than one (performed worse than expected), green indicates significantly less than one (performed better than expected). Because values have been exponentiated, they are interpreted as multiplicative.

**Table 4**
Models of gun violence by year, 2014–2017.

| Predictor | Main effects (without interaction) | | | | With interaction | | | |
|---|---|---|---|---|---|---|---|---|
| | 2014 | 2015 | 2016 | 2017 | 2014 | 2015 | 2016 | 2017 |
| *Socio-Economic factors (county-level)* | | | | | | | | |
| Income inequality | 0.08 | 0.07 | 0.09* | 0.08* | 0.09* | 0.07 | 0.08 | 0.08 |
| Median Income | −0.21* | −0.21* | −0.23* | −0.27* | 0.02 | 0.06 | −0.03 | −0.05 |
| Proportion below poverty line | −0.09 | −0.05 | −0.08 | −0.05 | 0.12 | 0.20* | 0.12 | 0.15 |
| Proportion college graduates | 0.02 | 0.00 | −0.01 | −0.01 | 0.01 | 0.00 | 0.15 | 0.00 |
| Proportion married | −0.13* | −0.09 | −0.11* | −0.09 | −0.10 | −0.08 | −0.06 | −0.07 |
| Degree urban | 0.40* | 0.35* | 0.36* | 0.38* | 0.36* | 0.32* | 0.30* | 0.35* |
| Minority population | 0.21* | 0.20* | 0.20* | 0.23* | 0.20* | 0.20* | 0.20* | 0.20* |
| Crime rate | 0.10* | 0.14* | 0.11* | 0.13* | 0.09* | 0.13* | 0.13* | 0.12* |
| *Community gun factors (state-level)* | | | | | | | | |
| 2014 Gun law restrictiveness | −0.26* | −0.20 | −0.16 | −0.09 | −0.27* | −0.23* | −0.16 | −0.08 |
| 2014 Gun ownership | −0.04 | 0.03 | 0.13 | 0.10 | −0.05 | 0.05 | 0.17 | 0.12 |
| *Altitude (county-level)* | | | | | | | | |
| Elevation | −0.03 | −0.03 | −0.08 | −0.03 | −0.03 | −0.03 | −0.07 | −0.02 |
| *Interaction* | | | | | | | | |
| Median income × Poverty | – | – | – | – | 0.13* | 0.14* | 0.13* | 0.13* |
| *Intercept* | −0.52* | −0.33* | −0.22 | −0.15 | −0.38* | −0.26* | −0.34* | −0.07 |

*Note.* There are 3120 counties in the analysis; the dependent variable is gun violence incidence (casualties including injuries and killings). Entries are coefficients from zero-inflated Poisson generalized linear mixed-effects models, in which all predictors are entered simultaneously. Because all predictors are standardized, coefficients' relative magnitude is indicative of relative contribution to the prediction of incidence. Two other interactions detected by the CART analysis are excluded because they proved non-significant in models that included all three of the interactions. *99.5% credibility interval does not include zero.

that allow for a more complete analysis, which captures different time periods more completely. Despite these limitations, this study uses two complementary methods for examining community-level socioeconomic, spatial variables to analyze gun violence rates and identifies several important predictors. With around 150,000 firearm deaths reported by the CDC over these four years, it is important to understand where gun violence is occurring, what factors are strongly linked to high levels of gun violence, and how it might be prevented.

Results of the spatial distribution of these residuals show that there are places that do better than expected, which might be labeled "cool" spots, or worse than expected, or "hot" spots (see Figs. 3 and 4). Such results may have important implications for future research. Specifically, a study of cool spots might reveal factors that are crucial for maintaining low gun violence rates but that were not examined in the current study (e.g., community-building activities; gun violence intervention programs; amount of green space; police-community trust). The same can be said for hot spots, as some factors likely make gun violence even worse than the current models could examine (e.g., lack of collective efficacy; police-community mistrust). The existence of systematic residuals over time is something that deserves more attention: Such residuals might reflect non-linearities in the variables that were studied (perhaps some factors should be examined logarithmically, e.g., rather than linearly), reflect extremes on variables we examined that are not captured by community-level factors, or reflect variables that were not incorporated into the current study (e.g., green space).

In our Introduction, we noted two studies that are exceptions about temporal trends in gun violence research. First, Siegel et al. (2013) examined 30-year trends at the state level, whereas the current study examines gun violence in each of four years, but it does not directly model temporal trends, which may be valuable for future research, especially as more waves are available from the GVA. Second, Ousey (2017) examined homicides generally, rather than homicides by guns per se, that occurred between 2006 and 2010 for 524 large U.S. counties, those with populations of at least 100,000 persons in the 2000 census. The current research expands these previous studies by directly comparing counties regardless of population size and directly examining gun violence. Our work has shown that population size is a key factor for gun violence, but future work could, as noted, be more fine-grained.

Future research also should examine a wider variety of predictors, including new geographic, socioeconomic, and gun-related data. It would be useful to examine factors such as gentrification rates, police-community relations, racial segregation, accessibility to public services, gun violence intervention programs, and gun ownership at the county-level, including both registered and unregistered firearms across racial groups. While examining new data, new interactions could be tested and interpreted beyond what was seen here. Expanding the length of time that the study considers, and determining how gun laws change over time and how well they are implemented will allow for an interesting temporal analysis of how impactful public policy is on firearm incidents.

### 4.2. Policy implications

Gun ownership did not significantly predict gun violence. However, state-level gun law restrictiveness significantly reduced gun violence in the first years of our study, but this factor's importance declined over time. This reduction in impact may be a byproduct of our measurement of gun law restrictiveness at one point in time, which does not reflect subsequent changes in gun laws to loosen or strengthen gun regulations. It also does not address how well gun laws are *implemented*, something future research should address.

Structural factors such as concentrated poverty in areas with higher median incomes as well as proportion of racial minorities in areas with high-income inequality were robustly associated with gun violence. These may well serve as proxies for racial segregation associated with concentrated disadvantage and institutional racism. The importance of these structural factors emphasizes the need for greater anti-poverty measures such as increased educational and economic opportunities, improvement of physical structures, and increasing amounts of green space. Although not examined here, it is sensible that gun violence will decrease as police-community relations improve, which includes building trust and decreasing the over-policing of these communities, as well as promoting community organizations and gun violence intervention programs that can divert those at risk of committing or being the victim of community gun violence to community organizations that can improve lives rather than exacerbate systemic factors such as mass incarceration. These efforts ought to go a long way toward reducing community gun violence (Bernstein, 2021; Braga et al., 2018; Butts et al., 2015; O'Brien et al., 2020; Sierra-Arevalo et al., 2017). Further research on hot and cool spots such as Fig. 3 identifies (aided as well by more nuanced models of racial segregation) could test the effectiveness of a variety of community-based gun violence prevention efforts designed to reduce community gun violence (e.g., McMillan and Bernstein, 2021).

## 5. Conclusions

The current research focused on four consecutive years of gun violence in the U.S. showed robust patterns whereby community-level features, specified at either county or state levels, are associated with gun violence, defined as incidence or in terms of casualties. Counties with income inequality are more likely to experience gun violence especially when a critical mass of poverty is present. Such results suggest where interventions should focus if they are to reduce levels of gun violence in the U.S.

## Authorship credit statement

Blair T. Johnson: All aspects from conceptualization through writing. Anthony Sisti: Data analyses, write-up. Mary Bernstein: Write-up. Kun Chen: Data analyses, write-up. Emily A. Hennessy: Write-up. Rebecca L. Acabchuk: Write-up. Michaela Matos: Data collection, write-up. All authors agree to the content of this submission.

## Declaration of competing interest

The authors declare no conflicts of interest.

## Acknowledgments

This research was supported by the University of Connecticut's College of Liberal Arts and Sciences' Bennett Fund for Innovative Education in Health and Society. Preliminary versions of this study were reported in the undergraduate honor's theses of Michaela Matos and Anthony Sisti. We also thank those responsible for sharing sources of data for this analysis, including the Gun Violence Archive, the U.S. Census Bureau, the Inter-University Consortium for Political and Social Research, and the U.S. Geologic Survey. We thank Ankit Rastogi for providing U.S. racial segregation data and Saniya Lakhiani for assistance with the references.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2021.113969.

## References

Abrutyn, Seth, Mueller, Anna S., 2018. Toward a cultural-structural theory of suicide: Examining excessive regulation and its discontents. Sociol. Theory 36 (1), 48–66.
Abt, T., 2019. Bleeding Out: the Devestating Consequences of Urban Violence– and a Bold New Plan for Peace in the Streets. Basic Books.
Alexander, M., 2020. The New Jim Crow: Mass Incarceration in the Age of Colorblindness. The New Press.
Anderson, E., 2000. Code of the Street: Decency, Violence, and the Moral Life of the Inner City. WW Norton & Company.
Bakka, H., Rue, H., Fuglstad, G., Riebler, A., Bolin, D., Illian, J., Lindgren, F., 2018. Spatial modeling with R-INLA: a review. Wiley Interdiscipl. Rev. – Comput. Stat. 10 (6), e1443.
Banerjee, S., Carlin, B.P., Gelfand, A.E., 2014. Hierarchical Modeling and Analysis for Spatial Data. CRC press. https://doi.org/10.1201/b17115.
Bernstein, M., 2021. Armed Intimidation, Police Violence, and the Gun Violence Prevention Movement. Retrieved from: https://mobilizingideas.wordpress.com/2021/01/20/armed-intimidation-police-violence-and-the-gun-violence-prevention-movement/.
Besag, J., 1974. Spatial interaction and the statistical analysis of lattice systems. J. Roy. Stat. Soc. B – Methodol. 36 (2), 192–225.
Besag, J., York, J., Mollié, A., 1991. Bayesian image restoration, with two applications in spatial statistics. Ann. Inst. Stat. Math. 43 (1), 1–20.
Bland, J. Martin, Altman, Douglas G., 2011. Correlation in restricted ranges of data. BMJ 342, d556.
Blangiardo, M., Cameletti, M., Baio, G., Rue, H., 2013. Spatial and spatio-temporal models with R-INLA. Spatial and Spatio-Temporal Epidemiol. 4, 33–49. https://doi.org/10.1016/j.sste.2012.12.001.
Brady, Campaign, 2015. State Scorecard 2014: State Gun Laws. Author, Washington, DC.
Braga, A.A., Weisburd, D., Turchan, B., 2018. Focused deterrence strategies and crime control: an updated systematic review and meta-analysis of the empirical evidence. Criminol. Publ. Pol. 17 (1), 205–250.
Brenner, B., Cheng, D., Clark, S., Camargo Jr., C.A., 2011. Positive association between altitude and suicide in 2584 US counties. High Alt. Med. Biol. 12 (1), 31–35. https://doi.org/10.1089/ham.2010.1058.
Butts, J.A., Roman, C.G., Bostwick, L., Porter, J.R., 2015. Cure violence: a public health model to reduce gun violence. Annu. Rev. Publ. Health 36, 39–53.
Cabrera, J.F., Kwon, R., 2018. Income inequality, household income, and mass shooting in the United States. Front. Publ. Health 6, 294. https://doi.org/10.1080/09581596.2017.1383599.
Carter, T.J., Parker, K.F., Zaykowski, H., 2017. Building bridges: linking old heads to collective efficacy in disadvantaged communities. Sociol. Forum 32, 1093–1111.
Desmond, M., Valdez, N., 2013. Unpolicing the urban poor: consequences of third-party policing for inner-city women. Am. Sociol. Rev. 78 (1), 117–141.

Dotsquare, 2018. Retrieved from: https://www.geocod.io/.
Fagan, J., Wilkinson, D.L., Davies, G., 2007. Social contagion of violence. In: Flannery, D., Vazsonyi, A., Waldman, I. (Eds.), The Cambridge Handbook of Violent Behavior. Cambridge University Press, pp. 688–723.
Garland, D., 2001. The Culture of Control: Crime and Social Order in Contemporary Society. University of Chicago Press, Chicago.
Geier, D.A., Kern, J.K., Geier, M.R., 2017. A longitudinal ecological study of household firearm ownership and firearm-related deaths in the United States from 1999 through 2014: a specific focus on gender, race, and geographic variables. Prev. Med. Rep. 6, 329–335.
GVA, 30 July 2019. About Gun Violence Archive. Retrieved from: https://www.gunviolencearchive.org/about.
Heath, Melanie, 2020. One Marriage Under God: The Campaign to Promote Marriage in America. NYU Press, New York.
Hinton, E., 2016. From the War on Poverty to the War on Crime: the Making of Mass Incarceration in america. Harvard University Press, Cambridge.
Jackson, D.B., Fahmy, C., Vaughn, M.G., Testa, A., 2019. Police stops among at-risk youth: repercussions for mental health. J. Adolesc. Health 65 (5), 627–632.
Kalesan, B., Villarreal, M.D., Keyes, K.M., Galea, S., 2016. Gun ownership and social gun culture. Inj. Prev. – J. Int. Soc. Child Adolesc. Inj. Prev. 22 (3), 216–220. https://doi.org/10.1136/injuryprev-2015-041586.
Kennedy, B.P., Kawachi, I., Prothrow-Stith, D., Lochner, K., Gupta, V., 1998. Social capital, income inequality, and firearm violent crime. Soc. Sci. Med. 47 (1), 7–17.
Kennedy, D.M., 2011. Don't Shoot: One Man, a Street Fellowship, and the End of Violence in Inner-City america. Bloomsbury Publishing, USA.
Kim, N., Mickelson, J.B., Brenner, B.E., Haws, C.A., Yurgelun-Todd, D.A., Renshaw, P.F., 2011. Altitude, gun ownership, rural areas, and suicide. Am. J. Psychiatr. 168 (1), 49–54.
Kious, B.M., Kondo, D.G., Renshaw, P.F., 2018. Living high and feeling low: altitude, suicide, and depression. Harv. Rev. Psychiatr. 26 (2), 43–56. https://doi.org/10.1097/HRP.0000000000000158.
Kirk, D.S., Papachristos, A.V., 2011. Cultural mechanisms and the persistence of neighborhood violence. Am. J. Sociol. 116 (4), 1190–1233.
Kwon, R., Cabrera, J.F., 2019. Socioeconomic factors and mass shootings in the United States. Crit. Publ. Health 1–8. https://doi.org/10.1080/09581596.2017.1383599.
Lee, L.K., Fleegler, E.W., Farrell, C., Avakame, E., Srinivasan, S., Hemenway, D., Monuteaux, M.C., 2017. Firearm laws and firearm homicides: a systematic review. JAMA Intern. Med. 177 (1), 106–119.
Leitner, J.B., Hehman, E., Ayduk, O., Mendoza-Denton, R., 2016. Racial bias is associated with ingroup death rate for blacks and whites: insights from project implicit. Soc. Sci. Med. 170, 220–227.
Lindgren, F., Rue, H., 2015. Bayesian spatial modelling with R-INLA. J. Stat. Software 63 (19), 1–25.
Massey, D.S., 1995. Getting away with murder: segregation and violent crime in urban America. Univ. Penn. Law Rev. 143, 1203–1232.
McMillan, J., Bernstein, M., May 2021. Beyond gun control: mapping gun violence prevention logics. Sociol. Perspect. https://doi.org/10.1177/07311214211010845.
Menakem, R., 2017. My Grandmother's Hands: Racialized Trauma and the Pathway to Mending Our Hearts and Bodies. Central Recovery Press.
Merton, R.K., 1938. Social structure and anomie. Am. Sociol. Rev. 3 (5), 672–682.
O'Brien, T.C., Meares, T.L., Tyler, T.R., 2020. Reconciling police and communities with apologies, acknowledgements, or both: a controlled experiment. Ann. Am. Acad. Polit. Soc. Sci. 687 (1), 202–215.
Orchard, J., Price, J., 2017. County-level racial prejudice and the black-white gap in infant health outcomes. Soc. Sci. Med. 181, 191–198. https://doi.org/10.1016/j.socscimed.2017.03.036.
Ousey, Graham C., 2017. Crime is not the only problem: Examining why violence and adverse health outcomes co-vary across large US counties. J. Crim. Justice 50, 29–41.
Papachristos, A.V., Wildeman, C., Roberto, E., 2015. Tragic, but not random: the social contagion of nonfatal gunshot injuries. Soc. Sci. Med. 125, 139–150.
Pear, V.A., Castillo-Carniglia, A., Kagawa, R.M., Cerdá, M., Wintemute, G.J., 2018. Firearm mortality in California, 2000–2015: the epidemiologic importance of within-state variation. Ann. Epidemiol. 28 (5), 309–315 e2.
Pickett, K.E., Wilkinson, R.G., 2015. Income inequality and health: a causal review. Soc. Sci. Med. 128, 316–326.
Rios, V.M., 2011. Punished: Policing the Lives of Black and Latino Boys. NYU Press, New York.
Rue, H., Martino, S., Chopin, N., 2009. Approximate bayesian inference for latent Gaussian models by using integrated nested laplace approximations. J. Roy. Stat. Soc. B – Stat. Methodol. 71 (2), 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x.
Runciman, W.G., 1966. Relative Deprivation and Social Justice: A Study of Attitudes to Social Inequality in Twentieth-Century England. University of California Press, Berkeley, CA.
Sampson, R.J., Bartusch, D.J., 1998. Legal cynicism and (subcultural?) tolerance of deviance: the neighborhood context of racial differences. Law Soc. Rev. 32 (4), 777–804.
Sewell, A.A., Jefferson, K.A., 2016. Collateral damage: the health effects of invasive police encounters in New York city. J. Urban Health 93 (1), 42–67.
Sewell, A.A., Jefferson, K.A., Lee, H., 2016. Living under surveillance: gender, psychological distress, and stop-question-and-frisk policing in New York city. Soc. Sci. Med. 159, 1–13.
Siegel, M., Ross, C.S., King III, C., 2013. The relationship between gun ownership and firearm homicide rates in the United States, 1981–2010. Am. J. Publ. Health 103 (11), 2098–2105.
Sierra-Arevalo, M., Charette, Y., Papachristos, A.V., 2016. Evaluating the effect of project longevity on group-involved shootings and homicides in new haven, Connecticut. Crime Delinquen. 63 (4), 1–22.
Sierra-Arevalo, M., Charette, Y., Papachristos, A.V., 2017. Evaluating the effect of project longevity on group-involved shootings and homicides in new haven, Connecticut. Crime Delinquen. 63 (4), 446–467.
Simons, R.L., Lei, M.K., Beach, S.R., Philibert, R.A., Cutrona, C.E., Gibbons, F.X., Barr, A., 2016. Economic hardship and biological weathering: the epigenetics of aging in a US sample of black women. Soc. Sci. Med. 150, 192–200.
Sunshine, J., Tyler, T.R., 2003. The role of procedural justice and legitimacy in shaping public support for policing. Law Soc. Rev. 37 (3), 513–548.
Theide, Brian C., Kim, Hyojung, Slack, Tim, 2017. Marriage, Work, and Racial Inequalities in Poverty: Evidence From the United States. J. Marriage Family 79, 1241–1257.
Turney, K., 2020. Depressive symptoms among adolescents exposed to personal and vicarious police contact. Soc. Ment. Health. https://doi.org/10.1177/2156869320923095, 2156869320923095.
Wacquant, L., 2009. Punishing the Poor: the Neoliberal Government of Social Insecurity. Duke University Press, Durham.
Wilkinson, R., Pickett, K., 2011. The Spirit Level: Why Greater Equality Makes Societies Stronger. Bloomsbury Publishing, USA.
Wong, B., Bernstein, S., Jay, J., Siegel, M., 2020. Differences in racial disparities in firearm homicide across cities: the role of racial residential segregation and gaps in structural disadvantage. J. Natl. Med. Assoc. 112 (5), 518–530.