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Historic redlining, structural racism, and firearm violence: A structural equation modeling approach

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Abstract

Background: Firearm homicides disproportionately affect Black communities. Redlining – discriminatory lending practices of the early 20th century - are associated with current increased rates of firearm violence. Poverty and concentrated disadvantage are also associated with firearm violence. The interaction of these factors with racist redlining housing practices remains unclear.

Methods: We used generalized structural equation modeling to characterize the mediators through which redlining practices of the 1930s led to present rates of firearm violence in Boston using a negative binomial model. Principle component analysis was used to create four distinct mediating variables representing census block socioeconomic and built environment information, while reducing dimensionality. We calculated the direct effect between harmful (Red and Yellow) vs beneficial (Green) designations and firearm incident rate, indirect effect between redlining designation and firearm incident rate through each mediating variable, and the total effect. The percentage mediation of each mediator was subsequently calculated.

Findings: Red and Yellow areas of Boston were associated with an 11•1 (95% CI 5•5,22•4) and 11•4 (5•7,22•8) increased incident rate of shooting when compared to Green. In the pathway between Red designation and firearm incident rate, poverty and poor educational attainment mediated 20% of the interaction, share of rented housing mediated 8%, and Black share of the

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Contributors

MP and KK: conceptualization, methodology/analysis, interpretation, validation, supervision, writing -review and editing

MN: interpretation, writing- original draft, review and editing

TD and LA: interpretation, writing- review and editing

Declaration of interest

The authors have nothing to disclose.

Data sharing statement

All data in this study is publicly available to researchers.

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Supplementary materials

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population 3%. In the pathway between Yellow designation and firearm incident rate, poverty and poor educational attainment mediated 16% of the association, and Black share of the population mediated 13%.

Interpretation: Redlining practices of the 1930s potentially contribute to increased rates of firearm violence through changes to neighborhood environments, namely through preclusion from homeownership, poverty, poor educational attainment, and concentration (i.e. segregation) of Black communities. These downstream mediating factors serve as points for policy interventions to address urban firearm violence.

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Keywords

Firearm violence; Structural racism; Socioeconomic; Structural equation modeling; Health policy

1. Introduction

Firearm injuries remain a major source of morbidity and mortality in the United States. Despite a small dip in the number of intentional firearm injuries in the early 2010s, there has been a steady increase over the last few years [1]. There are substantive demographic differences among firearm deaths based on types of injury [2]. While older white men are overrepresented among firearm suicides, Black and brown men are vastly overrepresented among homicides, the leading cause of death for Black men under the age of 44 [3,4]. Much of the medical and criminology literature around firearm homicide prevention focuses on individual-level factors, such as the perpetrator's race, history of drug use, and firearm possession [5,6]. Geographic concentration of firearm incidents, however, would suggest that neighborhood-level factors, such as concentrated poverty and lack of social mobility, contribute to the epidemiology of firearm homicide [7,8].

Studies have reiteratively illustrated the overrepresentation of Black men in firearm homicides and assaults [9,10], but few have gone on to distinguish the underlying socioeconomic and built environment factors that contribute to these disparities. Often studies addressing disparities in firearm violence fail to identify race as a proxy for the effects of discriminatory policies. Urban firearm violence, in particular, affects Black and brown men because of the downstream effects of discriminatory housing policies, as illustrated in Philadelphia where historically redlined areas exhibit nearly 13-times higher rates of shooting compared to other areas [11]. Previous studies utilizing machine learning have separately outlined the impact of neighborhood level segregation, education, and poverty on the incidence of firearm violence [12]. History would suggest, however, that concentrated poverty and other neighborhood level factors are all direct consequences of historic racist housing policies [13].

Redlining, as it is colloquially known, describes discriminatory lending practices of the Home Owner's Loan Corporation (HOLC) during the New Deal era of the 1930s that effectively excluded Black Americans from obtaining government-backed home loans [14].

HOLC created residential security maps of urban areas that described the risk of investment in those areas. Areas with significant Black populations (redlined areas) were considered “hazardous” by HOLC standards and did not qualify for federally-backed loans [14,15].

Today, historically redlined areas still have higher Black shares of the population, lower home values, and higher poverty rates [13,16]. Poverty and socioeconomic factors have similarly been found to be independently associated with firearm violence and crime in general [17]. Studies have highlighted the impact of redlining on firearm violence, but there remains a paucity of literature seeking to characterize and clarify the mediating neighborhood level factors by which historic redlining and structural racism have led to higher rates of firearm violence in these areas. Our objective was to outline the mediating neighborhood-level socioeconomic and demographic factors that contribute to these observed disparities using a structural equation modeling approach from a single city (Figure 1). In identifying mediators in the causal pathway, we can develop targeted interventions.

2. Methods

2.1. Data sources

We obtained police incident report data from the Boston Police Department (BPD) between January 1, 2016 and December 31, 2019 [18]. BPD provides open-source information on all incidents within city limits for which police officers were dispatched along with geographic coordinates of the location of the incident. For the purposes of this study, data were limited to include those classified as assaults and homicides involving a firearm within the specified time period. This study was reviewed by the Institutional Review Board at Boston University Medical Center and deemed to be exempt.

Redlining vector files were obtained from *Mapping Inequality* through the University of Richmond [19]. This research group over-layed historic HOLC redlining maps from the late 1930s on current geographic coordinates to create vector files outlining these historic borders. HOLC grades included Green, Blue, Yellow, and Red and denoted incrementally higher risk of investment moving from Green to Red. Historically, Redlined areas were deemed “hazardous,” Yellow were considered “definitely declining,” Blue were considered “still desirable,” and Green was considered “best.” Collectively, Red and Yellow designated areas had a large or rising share of minorities and did not qualify for federally backed loans. There is further evidence that private lenders too precluded home loans for people living in these areas.

Boston city limit vector files were obtained from Boston Open-source [18].

2.2. Exposure of interest

The exposure of interest was HOLC grade as outlined above. HOLC classifications Blue, Yellow, and Red were compared to Green (and unclassified, n=1,725) areas as the reference group.

2.3. Outcomes of interest

The outcome of interest was rate of shooting (number of shootings divided by the population within the census block) for a particular census block population within the four-year study period.

2.4. Mediators of interest

Sociodemographic data were obtained at the census tract level from the 2010 decennial Census and 2017 5-year estimates of the American Community Survey (ACS). Given the historical devaluation of neighborhoods deemed hazardous by HOLC and evidence of the perpetuation of this devaluation through continued socioeconomic disparities [13,16], we sought to understand the downstream sociodemographic effects of redlining. Chosen studied variables included those that are known social determinants of health, themselves geographically concentrated in neighborhoods. Variables included Black share of the population, percentage of population below the poverty line, percentage with Supplemental Nutrition Assistance Program (SNAP) benefits, percentage uninsured, household income, Gini coefficient (a measure of income inequality), and percentage with less than high school degree. We did not assess any other crime data due to likely collinearity with the outcome of interest. Similarly, evidence of considerable concentration of firearm violence in Boston[7] would suggest that there is considerable spatial autocorrelation. However, given evidence of the concentration of poverty and other socioeconomic factors due to redlining practices [13], we did not control for spatial autocorrelation. This geographic concentration is likely a result or mediator of our exposure of interest and, as such, controlling for this factor would nullify the effect. Census block vector files were obtained from the U.S. Census Bureau.

2.5. Geospatial analysis

Boston assault and homicide incidents were mapped in ArcMap [20] using provided incident coordinates. These were spatially joined with census block designations, and further joined with the redlining vector files to assign a HOLC designation to each shooting. Census blocks were chosen as the geographic unit to study as this the smallest geographic area provided through the U.S. census and allowed us to obtain a more granular representation of redlined areas. Those areas without a specified HOLC designation were grouped with the reference category (Green) to maintain power given the low number of Green census blocks. As such, comparisons were between harmful (Red and Yellow) and beneficial (Green) designations. Shooting numbers were tabulated by census block and used to calculate shooting rates. Census blocks were then linked to census tract-level sociodemographic data as this is the smallest geographic unit that provides reliable socioeconomic information from the ACS, information that is not provided at the census block level. As such, multiple census blocks may represent the same census tracts and, therefore, socioeconomic census data. In total, 7,575 census blocks were identified representing 180 census tracts. Census blocks with no population residing in that area (such as commercial areas or unusable land) were excluded from the analysis, 45 in total. Of the 45 excluded, only one census block had a shooting. Of the 7530 included, 454 had one or more shooting. Local Moran's I was used to map the concentration of firearm violence in the city.

2.6. Theoretic and analytic framework

Structural Equation Modeling (SEM) was the basis for the overall analysis. SEM is a multivariable technique that incorporates multiple regression equations to study the association of different variables in a causal pathway. For the purpose of this study, we were interested in assessing the mediating effects of neighborhood (census block) socioeconomic, and demographic variables in the pathway between historical redlining and the incidence of firearm violence today. This technique allows one to calculate the direct association between two variables and the indirect association between an independent mediator. Taken together, these direct and indirect effects can be combined to assess the total effect, which represents all pathways between the exposure and outcome of interest.

Our hypothesized causal pathway was created based on historical knowledge of redlining and empirical studies of its continued effects on neighborhood socioeconomic and demographics [13,16]. We postulate that harmful redlining classification, as defined in the 1930s-40s redlining maps, has led to increased firearm violence today through the mediating effect of changes to the built environment including poverty, poor education, and need for public services that persist today. While we do not explicitly study the temporal changes to the built environment since the HOLC maps were created, studies have documented the persistence of these harmful changes [13]. This temporal association is the basis for the studied effects in this study.

2.7. Principal component analysis

We used principal component analysis (PCA) for the socioeconomic and demographic variables to reduce the dimensionality of the included variables. Full details of the PCA are provided in the supplement. A scree plot was generated to determine the optimal number of components and eigenvalues for each component were determined within a preset optimal number of clusters. Those with the largest eigenvalues within a certain cluster were selected. Mediating variables were created by taking the sum of the proportions of each contributing component (as determined by eigenvalues and eigenvectors). Mediating variables were analyzed prior to PCA and were normally distributed. Mediator one (M1) was a sum of the proportion of population below the poverty line, proportion with SNAP benefits, proportion with greater than 30% of their income going towards housing, proportion unemployed, and proportion with less than a high school degree. We term M1 “poverty, poor educational attainment, and need for public services”. Mediator two (M2) was the sum of the centile of house price and the Gini index (a measure of income inequality) of the area. We term M2, “housing affordability and income inequality.” M3 represents the “share of rented housing in an area” and represents the proportion of rented housing. Finally, M4 represents the “Black share of the population” and is the proportion of residents within an area identified as Black. All mediating variables were normalized around the mean and centered at zero with analyses based on increases in standard deviation of each of the variables for ease of comparison.

2.8. Structural equation modeling

We used generalized structural equation modeling, a variant of structural equation modeling, which provides flexibility in the modeling distributions and count data. This was used to identify multiple socioeconomic variables in the causal pathway between historic redlining

and current firearm violence. Given the large number of census blocks with zero shootings (94%), we were unable to use a linear regression model. We assessed model fit comparing Poisson, negative binomial, and zero inflated Poisson with negative binomial shown to consistently have a lower Akaike Information Criterion (AIC) score (2423 for negative binomial, 2443 for Poisson, 2460 for zero inflated Poisson, $p < 0.001$). Negative binomial models with robust error variance were then used to assess the incident rate ratio (IRR) in the direct and indirect pathways. The relationship between HOLC designation and the mediating variables created from the principal component analysis was evaluated in a Gaussian distribution. Our model was built using `gsem` in Stata 16, allowing for collinearity among covariates.

Estimating the mediating, or indirect effects, required several steps. The proposed causal pathway is presented in Figure 1. First, we calculated the direct association between each HOLC designation (Blue, Yellow and Red) when compared to Green classification (X) and shooting rate (Y). Given no crude difference between Blue and Green areas, no further mediating analysis was performed for Blue areas. We then calculated the indirect pathways between HOLC designation (X) and shooting rate (Y) by combining the nonlinear estimations of the direct pathway from redlining to the mediator (M1, M2, M3...) and the direct pathway from the mediator (M) to shooting rate (Y). The direct pathway between the exposure (X) and mediator (M) utilized a linear regression model, while the direct pathway between the mediator (M) and outcome (Y) utilized a negative binomial model. HOLC designation (X) was included as a categorical dummy variable comparing HOLC designations Blue, Yellow and Red to Green. All HOLC designations were included in the full model, but indirect pathways were not reported for Blue designations given no baseline differences in incidence of firearm violence. Mediators were included as continuous variables measured as standard deviations from the mean. Shooting rates were included as continuous variables (shooting incidents per 1,000 people). Total effect was calculated as the sum of the direct effect of each HOLC designation on the incident rate of shooting added to the indirect effect of each mediating variable. Finally, the proportion mediated by each of the mediating variables was calculated by dividing the indirect effect of each mediating variable (M) by the total effect.

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3. Results

We identified 7,575 Census blocks assigned a HOLC classification, 45 of which were excluded given no population, likely due to commercial or unusable land. Of those 45 blocks, only one had a shooting incident. In total, 7,530 census blocks were analyzed, representing 180 census tracts. There were significant differences between HOLC classification in all of the sociodemographic variables analyzed as shown in Table 1. Overall, the shooting rates were significantly higher in those blocks with Yellow (5•4 shootings per 1,000 people) and Red classification (5•3) as compared to 0•5 in Green ($p < 0•001$). Yellow blocks had the highest share of black population (31•0%) and Red the second highest

(19.4%) ($p < 0.001$). Yellow and Red classification had higher percentage of residents below the poverty line (13.8 and 17.0% respectively), uninsured (3.7% and 3.6% respectively), publicly insured (39.2% and 38.4%), and with less than high school degree (12.9% and 17.0%) (all $p < 0.001$).

A map of firearm incident rates in Boston is presented in Figure 2a with vector files of the 1930s redlining maps provided in Figure 2b. When compared to Green, there was no statistically significant increased incident rate of shooting in Blue designation when assessing the crude association (IRR 1.71, 95% CI 0.50, 5.82). Yellow designation was associated with a 11.4 (95% CI 5.7, 22.8) times increased incident rate of shooting and Red a 11.1 (95% CI 5.5, 22.4) increased incident rate of shooting, respectively, when compared to Green.

In the direct pathway between the mediators of interest and shooting rate ($M \rightarrow Y$, Table 2,3), there was a 1.86 (95% CI 1.28, 2.69) increased incident rate of shooting per standard deviation (SD) increase in M1 (poverty, poor educational attainment, and need for public services). M2 (housing affordability and income inequality) saw no significant direct increase in shooting rate (IRR 1.11, 95% CI 0.95, 1.28). M3 (share of rented housing) and M4 (share of black population) were associated with a 1.28 (95% CI 1.01, 2.08) and 1.46 (95% CI 1.20, 1.79) increased incident rate of shooting per increase in standard deviation of the variable in the direct pathway.

The direct pathway for Red classification (Table 2) was associated with 3.25 (95% CI 1.35, 7.85) increased incident rate of shooting when compared to Green, accounting for mediators. In the direct pathway between Red classification (X) and the mediators (M), Red classification was associated with a 0.59 increased SD of M1 when compared to Green (Coeff 0.59, SE 0.03, $p < 0.001$). There was a significant negative direct association between M2 (Coeff -0.35, SE 0.05, $p < 0.001$), and positive associations between M3 (Coeff 0.38, SE 0.03, $p < 0.001$) and M4 (Coeff 0.12, SE 0.03, $p < 0.001$). In assessing the indirect association of Red classification on shooting rate through the mediators ($X \rightarrow M \rightarrow Y$), Red classification was associated with an increased indirect incident rate of shooting through M1 (IRR 1.39, 95% CI 1.14, 1.70), M3 (IRR 1.15, 95% CI 1.01, 1.32), and M4 (IRR 1.05, 95% CI 1.01, 1.08), but had no significant indirect effect through M2 (IRR 0.96, 95% CI 0.91, 1.02). Of the significant mediating pathways, M1 accounted for 20% of the mediation, M3 8%, and M4 3%.

The direct pathway between Yellow classification (Table 3) was associated with a 4.1 times increased incident rate of shooting when compared to Green (95% CI 1.64, 10.3), accounting for the mediators. In the direct pathway between Yellow designation and the mediators of interest ($X \rightarrow M$), Yellow designation was associated with an increase of 0.49 standard deviations of M1 when compared to Green (Coef 0.49, SE 0.03, $p < 0.001$). There was a significant negative direct association between Yellow classification and M2 (coef -0.65, SE 0.04, $p < 0.001$) and M3 (coef -0.18, SE 0.03, $p < 0.001$). Yellow classification was also associated with an increase in M4 when compared to Green (coef 0.58, SE 0.03, $p < 0.001$). The indirect association between Yellow designation and shooting rate through the mediators ($X \rightarrow M \rightarrow Y$) showed a significant positive effect through M1 (IRR

1•31,95% CI 1•11,1•54) and M4 (IRR 1•25,95% CI 1•11,1•40), but no significant indirect effects through M2 (IRR 0•93,95% CI 0•85,1•03) and M3 (IRR 0•93,95% CI 0•87,1•01). Of the significant mediating pathways, M1 accounted for 16% of the mediation in this pathway and M4 13%.

4. Discussion

In the United States, a racialized and stigmatized narrative of individual culpability continues to surround firearm homicides, particularly in urban areas. The current study helps refute the idea of individual responsibility alone by highlighting the enduring impact of structural racism in the form of redlining and the downstream socioeconomic and built environment factors that contribute to the incidence of firearm violence to this day. Our findings in Boston build on those from other cities, such as Philadelphia [11], revealing the mediating effect of changes to the built environment on the association of redlining on the incidence of firearm violence.

For both the “harmful” Red and Yellow designated areas in Boston, we show that shooting rates are significantly higher when compared to the historically “desirable” Green areas. These harmful designated neighborhoods would have largely been composed of minority residents at the time of the creation of the HOLC residential security maps and would not have qualified for federally backed home loans. We did not assess mediation for Blue designated areas as there was no baseline difference in incident rate of shooting between Blue and Green designations. Additionally, our analysis shows poverty and need for public services to be the most important contributing mediators in the causal pathway between these harmful HOLC designations and incidence of firearm violence. Exclusion from home loans during the New Deal era through government-backed organizations like the Home Owner’s Loan Corporation (HOLC) directly led to large wealth gaps between Black and white Americans. This is particularly noticeable in Boston where white residents have approximately \$250,000 in assets on average while Black residents have \$8 [21]. Sociologic studies suggest that inability to secure financial resources as a result of high unemployment or low wages lead to higher rates of illicit activity in order to generate income [22]. Our findings reinforce this idea by showing the collinearity of poverty, unemployment, and need for government services and their mediation in the causal pathway leading to increased firearm violence. An immediate historical example is drug trade in minoritized urban communities that is both a result of and a conduit for poverty through community disorganization and subsequent mass incarceration [23]. Preclusion of quality education, job ceilings, and low income wages resulting from redlining has led to significant intergenerational poverty and limited social mobility [13,16,24].

Our findings reinforce the detrimental effects of redlining policies on homeownership by showing tract-level percentage of rented housing to be important in the causal pathway between redlining and shooting rates. This is consistent with historical preclusion of Black families from government-backed home loans and lending discrimination that continues to this day. Restrictive housing covenants and overt racist lending practices set the stage for devaluation of Black communities through geographic concentration of intergenerational

poverty, poor education, and dismal social mobility within these intentionally blighted communities [13,14,16].

It is important to note that while we do not directly study the race of the victims of these shooting incidents due to limitations of the dataset, previous data would suggest that victims are disproportionately minoritized [25]. Interestingly, Black share of the population at the census tract level was shown to be more important in the incidence of firearm violence in HOLC-defined Yellow (definitely declining) areas, more than Red (hazardous). While not studied here, this could be reflective of gentrification (particularly in areas with good public transportation) leading to displacement of Black residents into Yellow-lined areas, which are largely adjacent to Red areas in Boston [26]. This may be reflective of the segregation of Black residents and resultant segregation within blighted areas. It is important to note that Black share of the population is likely representative of the continued discrimination that this socially constructed group experiences. In addition to concentrated poverty, research would suggest that Black assets are inherently devaluated when compared to white assets, suggesting that poverty could follow Black concentration simply through means of valuation and continued housing discrimination [27,28]. These issues are not studied here, but should be considered in future research.

While gun control measures have been shown to decrease rates of firearm suicides and mass casualties, there is conflicting evidence of reduction in firearm homicides [29]. Our findings would suggest that, in addressing firearm violence among minoritized communities, structural racism and its downstream effects inherent to the etiology of firearm violence will need to be concurrently addressed. Segregation from redlining alone does not lead to these disparities and, as such, the solutions will not come from desegregation alone. Our study highlights the need for solutions that target downstream effects of redlining practices, including poverty and lack of wealth. Redlining and segregation affect health in a multitude of ways and gun violence victimization is no different.

Despite the differences in the important mediating pathways in the different HOLC designations, the studied mediators accounted for only about 30% of the association between HOLC designation and the outcomes of interest. There are likely other unmeasured mediators that are not captured in this pathway, such as asset valuation and continued housing discrimination among displaced persons as discussed previously [27,28]. Additionally, the census-tract level measurements may lose some granularity of the neighborhood measures and we may not be fully appreciating the full mediation. The area of concentration of firearm incidents may be too small and guised by the larger census tract measures on which this study was based [7]. Gentrification in many of these areas may additionally distort the measured poverty and demographic data at the Census tract level. However, this analysis shows glimpses into some of the socioeconomic mechanisms by which structural racism exerts its effects. Further studies will need to clarify concentration of these deleterious socioeconomic factors and incidence of firearm violence.

Our study has some important limitations. It is observational retrospective data, therefore we would caution interpretation of causation. We only study incidents where firearms were involved in homicides and assaults, but were unable to ascertain incidents where firearms

were discharged without bodily harm which could also impact these communities. GSEM allows us to understand the mediating pathways between exposure and outcome. However, when using this type of model for causal inference, there is a lack of proper post-estimation methods. Additionally, despite the spatial features of our data, in assessing the causal structure, we were not able to account for spatial variance within this framework. We did not include temporal trends in the studied variables, as we used as outcome the sum of the incidents over time. The socioeconomic and demographic variables from the Census were available for the 2010 decennial Census and 2017 5-year estimates, while the outcome was 2016- 2019. Although the socioeconomic and demographic variables are likely to remain similar over this relatively short period, we cannot exclude possible residual confounding.

5. Conclusion

The pathways that lead to firearm violence in blighted communities extend far beyond the individual. In the current study, we show some of the important mediating pathways between redlining and the incidence of firearm violence today. Racist housing policies have had direct consequences on the socioeconomic and demographic makeup of urban neighborhoods. These, in turn, have led to the disproportionate firearm victimization of, particularly, young Black men in these communities. While race has been used to study differences in risk of exposure to firearm violence, our findings suggest it is a proxy for socioeconomic and policy factors, including racist housing practices and segregation. To address the disparate incidence of firearm violence across the country, continued efforts are needed to address the downstream effects of structural racism (poverty, preclusion from homeownership and segregation as shown in this study) through reparative solutions focused on reinvestment in these communities.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Research in context

Evidence before this study

We reviewed the medical, criminology and sociology literature through focused searches of PubMed and Google scholar to understand the built environment factors associated with urban firearm violence. Much of the available literature focuses on individual-level factors that are often based in racist stereotypes and reinforce pro-carceral ideas about crime and violence in American inner cities. Previous studies have highlighted extreme concentration of firearm violence in the city of Boston with about 3% of street blocks representing over half of the gun violence incidents. Similarly, studies out of Philadelphia have shown that historically redlined areas (defined as areas with large minority populations that were deprived of government-backed home loans in the 1930s) have much higher rates of firearm violence. Evidence suggests that redlining has led to detrimental socioeconomic factors, particularly for Black Americans that are concentrated in these neighborhoods. However, no studies have documented the mediating effects of these socioeconomic and neighborhood factors related to devaluation from redlining practices on the incidence of firearm violence today.

Added value of this study

The findings from the current study outline the neighborhood-level factors that mediate the relationship between structurally racist forces in the form of redlining and the current incidence of firearm assaults and homicides in an urban American city. We show that poverty and need for public services, high rates of rented housing, and concentration of Black residents (high percentage of Black residents) mediate this relationship. These mediators are representative of the larger segregation practices of redlining that separated Black Americans into certain areas of cities, prevented redlined communities from homeownership, which has led to significant intergenerational poverty. It is this intergenerational poverty and lack of social mobility that leads to high rates of crime, and subsequently firearm incidents..

Implications of all the available evidence

While much of the current literature and narrative focuses on legislative control of firearms, our findings suggest that addressing structural racism and its perpetuation will need to occur in order to decrease the rates of firearm homicides in American cities. This highlights the downstream factors of structural racism, such as poverty, homeownership, and segregation that have contributed to the rates of firearm incidents today, which allows targeted interventions in the future.

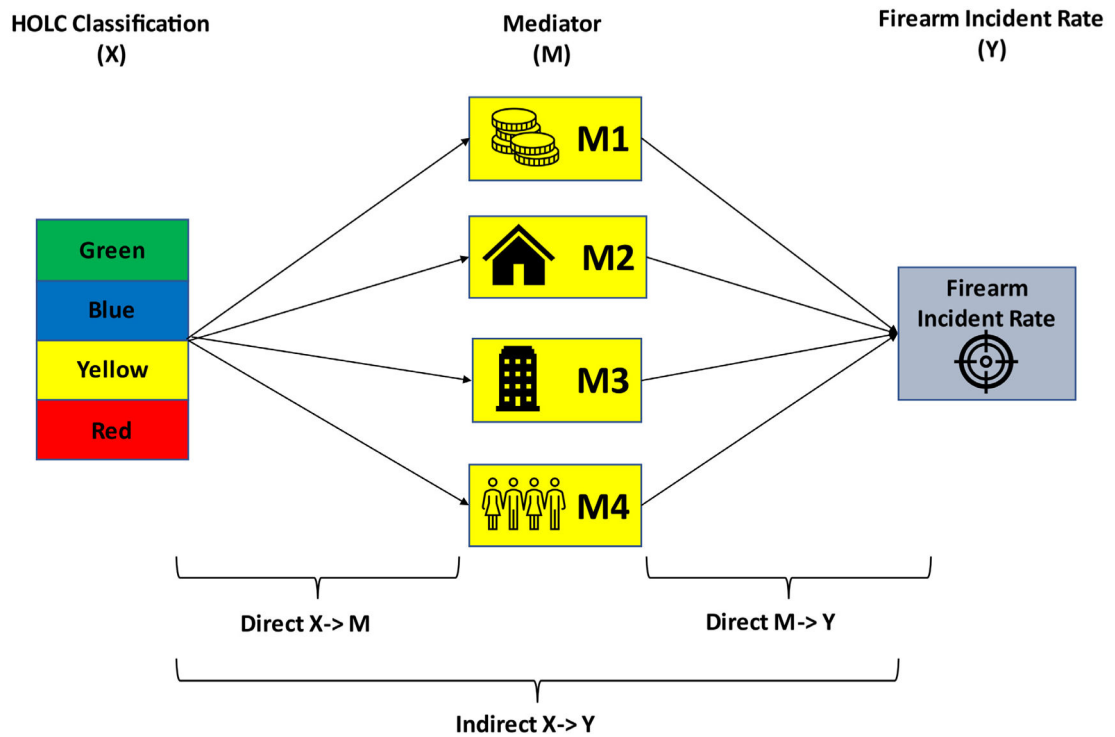


Figure 1. Theoretical framework on which Structural Equation Model was built. Harmful HOLC designations (Yellow and Red) were compared to Green as the reference group in the direct pathway between HOLC classification (X) and the firearm incident rate (Y), the direct pathway between HOLC classification (X) and the mediator of interest (M), the direct pathway between the mediator of interest (M) and firearm incident rate (Y), and finally the indirect pathway from HOLC designation (X) to firearm incident rate (Y) through each mediator (M) of interest.

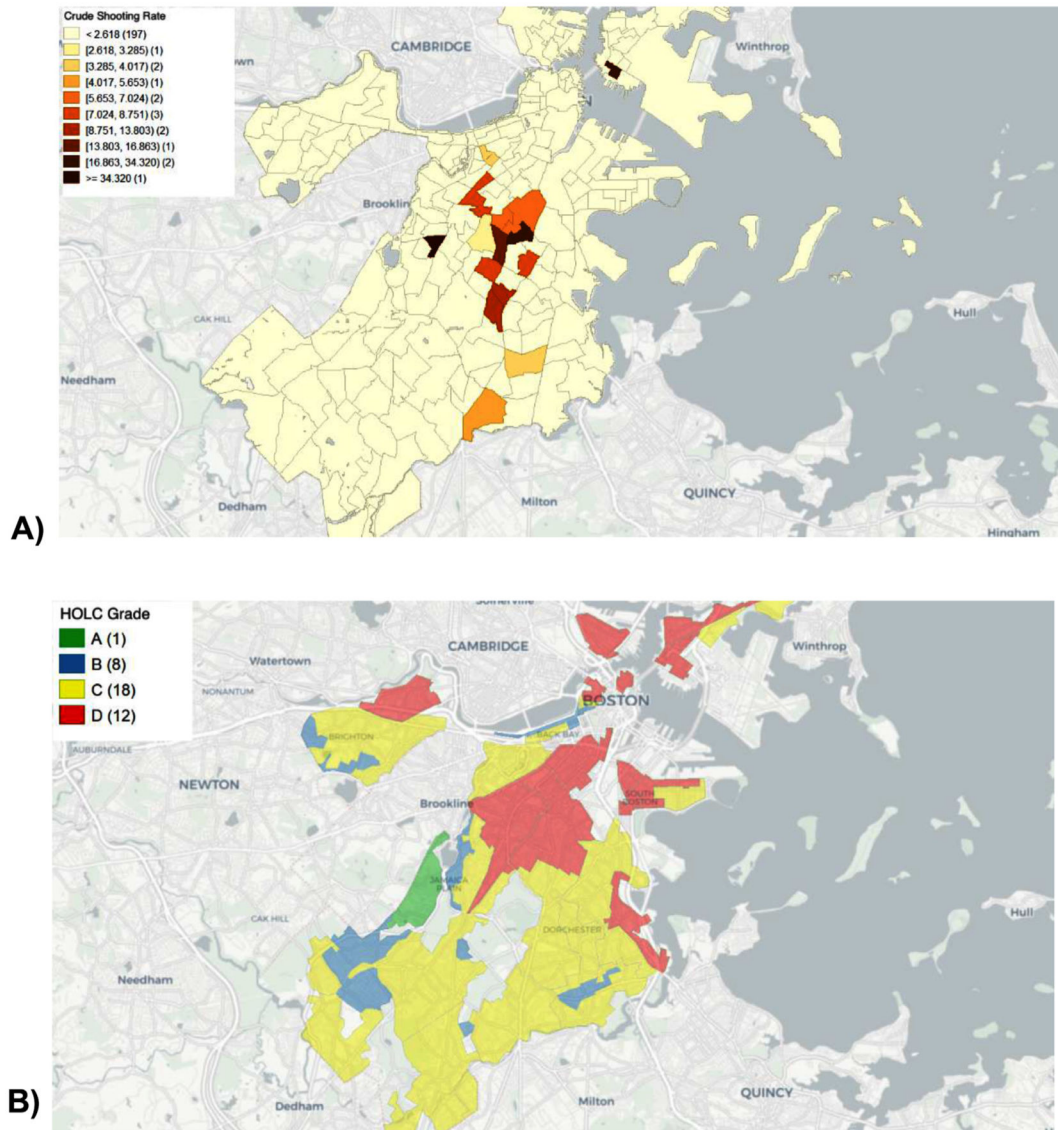


Figure 2.
A) Crude shooting rates (per 1,000 people) in Boston between 2016-2019 by Census tract and B) vector representation of original 1930s HOLC redlining map of Boston.

Table 1

Baseline census block characteristics by HOLC classification.

	HOLC Classification					P-value
	Green(n=1805)	Blue(n=455)	Yellow(n=3236)	Red(n=2034)		
Firearm Incident Rate (per 1,000 people), mean (SD)	0•5 (0•87)	0•8 (0•77)	5•4 (2•69)	5•3 (2•56)		<0•001
% Black, mean (SD)	16•4 (19•6)	11•2 (19•5)	31•0 (28•4)	19•4 (21•4)		<0•001
% Male, mean (SD)	54•7 (11•1)	46•8 (3•3)	47•3 (4•1)	49•4 (5•3)		<0•001
Age, mean (SD)	39•2 (6•2)	41•8 (5•3)	38•9 (5•1)	37•7 (3•9)		<0•001
% below poverty level, mean (SD)	10•7 (10•4)	6•1 (6•2)	13•8 (10•9)	17•0 (11•6)		<0•001
% with SNAP benefits, mean (SD)	13•2 (10•7)	7•4 (7•5)	20•2 (14•0)	23•0 (14•9)		<0•001
% with 30% or more of income going toward housing, mean (SD)	41•5 (12•8)	35•0 (8•1)	43•7 (10•8)	43•1 (11•0)		<0•001
% Uninsured, mean (SD)	3•0 (2•9)	2•0 (1•7)	3•7 (2•2)	3•6 (2•5)		<0•001
% with public insurance, mean (SD)	32•6 (19•7)	27•0 (10•9)	39•2 (17•8)	38•4 (17•9)		<0•001
% of labor force unemployed, mean (SD)	10•1 (9•7)	5•6 (2•7)	7•5 (4•6)	7•5 (5•5)		<0•001
% with less than high school degree, mean (SD)	9•5 (9•7)	5•6 (4•6)	12•9 (9•1)	17•0 (11•9)		<0•001
Household income (in 1000s of dollars), mean (SD)	108 (34)	118 (21)	88 (26)	91 (35)		<0•001
Gini index, mean (SD)	0•49 (0•09)	0•46 (0•07)	0•46 (0•06)	0•50 (0•08)		<0•001
Housing price (1000s of dollars), mean (SD)	1209 (541)	1017 (574)	932 (581)	1047 (625)		<0•001
% of rented housing, mean (SD)	62•4 (22•0)	43•0 (18•9)	58•9 (18•5)	70•1 (15•2)		<0•001
Rent, mean (SD)	2132 (720)	2023 (766)	1432 (666)	1560 (848)		<0•001

SEM model comparing shooting rates in HOLC Red vs Green areas in Boston in the A) direct pathway between HOLC Red (vs Green) designation and shooting rate accounting for mediators B) direct pathway between HOLC Red (vs Green) designation and the mediators (M_x), C) direct pathway between the mediators and shooting rate and D) Indirect pathway from HOLC Red (vs Green) designation to shooting rate through the mediators (M_x) of interest.

Table 2

	A) Direct		A) Indirect		Percent mediated (%)
	HOLC Red → Firearm Incident Rate (IRR, 95% CI)	M_x → Firearm Incident Rate (IRR, 95% CI)	HOLC Red → M_x (Coefficient, 95% CI)	HOLC Red → Firearm Incident Rate (IRR, 95% CI)	
HOLC Designation: Red (vs Green)	3•25* (1•35, 7•85)				
M1 (poverty, poor educational attainment, and need for public services)	0•59 (0•52, 0•66) p<0.001	1•86 (1•28, 2•69) p<0.001	0•59 (0•52, 0•66) p<0.001	1•39 (1•14, 1•70) p<0.001	20
M2 (housing affordability and income inequality)	-0•35 (-0•44, -0•26) p<0.001	1•11 (0•95, 1•28) p=0.13	-0•35 (-0•44, -0•26) p<0.001	0•96 (0•91, 1•02) p=0.14	8
M3 (Share of rented housing)	0•38 (0•32, 0•45) p<0.001	1•45 (1•01, 2•08) p=0.01	0•38 (0•32, 0•45) p<0.001	1•19 (1•04, 1•36) p=0.01	3
M4 (Black share of the population)	0•12 (0•07, 0•17) p<0.001	1•46 (1•20, 1•79) p<0.001	0•12 (0•07, 0•17) p<0.001	1•05 (1•01, 1•08) p=0.01	

Green= "Best", Blue= "Still Desirable," Yellow= "Definitely Declining," Red= "Hazardous"

Table 3

SEM model comparing shooting rates in HOLC Yellow vs Green census blocks in Boston in the A) direct pathway between HOLC designation and shooting rate accounting for mediators B) direct pathway between HOLC Yellow (vs Green) and the mediators, C) direct pathway between mediators and shooting rate and D) Indirect pathway from HOLC Yellow (vs Green) designation to shooting rate through the mediators (M_x) of interest.

	A) Direct	A) Direct	A) Indirect	Percent mediated (%)
HOLC Designation: Yellow (vs Green)	HOLC Yellow (X) → Firearm Incident Rate (Y)(IRR, 95% CI) 4*10** (1*64, 10*3)	M_x → Firearm Incident Rate (Y) (IRR, 95% CI) 1*86 (1*28, 2*69) p<0.001	HOLC Yellow (X) → Firearm Incident Rate (Y)(IRR, 95% CI) 1*31** (1*12, 1*53) p<0.001	
M1 (poverty, poor educational attainment, and need for public services)	HOLC Yellow (X) → M_x (Coefficient, 95% CI) 0*49 (0*43, 0*55) p<0.001	M_x → Firearm Incident Rate (Y) 1*11 (0*95, 0*25) p = 0.13	HOLC Yellow (X) → Firearm Incident Rate (Y)(IRR, 95% CI) 0*93 (0*85, 1*03) p = 0.13	16
M2 (housing affordability and income inequality)	-0*65 (-0*74, -0*57) p<0.001	1*28 (1*01, 2*08) p=0.01	0*93 (0*87, 1*01) p=0.20	
M3 (Share of rented housing)	-0*18 (-0*25, -0*12) p<0.001			
M4 (Black share of the population)	0*58 (0*53, 0*63) p<0.001	1*46 (1*20, 1*79) p<0.001	1*25** (1*11, 1*40) p<0.001	13

Green= "Best", Blue= "Still Desirable," Yellow= "Definitely Declining," Red= "Hazardous"