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## Neighborhood segregation, tree cover and firearm violence in 6 U.S. cities, 2015–2020

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### Abstract

Neighborhood segregation by race and income is a structural determinant of firearm violence. Addressing green space deficits in segregated neighborhoods is a promising prevention strategy. This study assessed the potential for reducing firearm violence disparities by increasing access to tree cover. Units of analysis were census tracts in six U.S. cities (Baltimore, MD; Philadelphia, PA; Richmond, VA; Syracuse, NY; Washington, DC; Wilmington, DE). We measured segregation using the index of concentration at the extremes (ICE) for race-income. We calculated proportion tree cover based on 2013–2014 imagery. Outcomes were 2015–2020 fatal and non-fatal shootings from the Gun Violence Archive. We modeled firearm violence as a function of ICE, tree cover, and covariates representing the social and built environment. Next, we simulated possible effects of “tree equity” programs, *i.e.*, raising tract-level tree cover to a specified baseline level.

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#### CRedit authorship contribution statement

**Jonathan Jay:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Michelle C. Kondo:** Conceptualization, Methodology, Writing – review & editing. **Vivian H. Lyons:** Writing – review & editing. **Emma Gause:** Writing – review & editing. **Eugenia C. South:** Conceptualization, Methodology, Writing – review & editing.

#### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ypmed.2022.107256>.

In our fully-adjusted model, higher privilege on the ICE measure (1 standard deviation, SD) was associated with a 42% reduction in shootings (incidence rate ratio (IRR) = 0.58, 95% CI [0.54, 0.62],  $p < 0.001$ ). A 1-SD increase in tree cover was associated with a 9% reduction (IRR = 0.91, 95% CI [0.86, 0.97],  $p < 0.01$ ). Simulated achievement of 40% baseline tree cover was associated with reductions in firearm violence, with the largest reductions in highly-deprived neighborhoods. Advancing tree equity would not disrupt the fundamental causes of racial disparities in firearm violence exposure, but may have the potential to help mitigate those disparities.

## Keywords

Firearm violence; Residential segregation; Racial disparities; Tree cover; Green space

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## 1. Introduction

The public health crisis of firearm injuries in the U.S. is worsening, recently surpassing traffic collisions as the leading cause of death among children and teens (Lee et al., 2022). Interpersonal firearm violence, in particular, has spiked since the beginning of the COVID-19 pandemic. This spike has further exacerbated longstanding racial disparities in firearm victimization (Pino et al., 2022) and exposure to firearm violence (Martin et al., 2022). Black youth experience the most severe disparities in both firearm victimization and exposure to firearm violence, with lifelong health consequences (Sheats et al., 2018).

Disparities in firearm violence exposure are strongly associated with residential racial segregation (Wong et al., 2020; Knopov et al., 2019; Krieger et al., 2017; Jacoby et al., 2018a; Poulson et al., 2021; Schleimer et al., 2021). Residential segregation is a fundamental cause of health disparities (Williams and Collins, 2001) because it concentrates social deprivation and privilege at the community level. A particularly strong predictor of firearm violence appears to be spatial polarization by both race (Black-White) and income (poor-affluent) (Krieger et al., 2017). When these dimensions of social deprivation and privilege are polarized, members of disadvantaged racial groups are more likely to live in communities with inferior access to government services, educational and employment opportunities, and a safe built environment.

Consequently, one promising strategy to address violence-related disparities is to improve the built environment through neighborhood greening, *i.e.*, increasing the density of parks, trees, and other green spaces and healthy vegetation. Recent work has found that adding and maintaining lot-sized green spaces reduced nearby firearm violence, particularly in the most economically disadvantaged neighborhoods (Branas et al., 2018). Like firearm violence patterns, greenness patterns closely align with boundaries drawn by historical institutional racial discrimination (*e.g.*, redlining (Jacoby et al., 2018b; Locke et al., 2021; Nardone et al., 2021)) and reinforced by contemporary segregation (Krieger et al., 2017), since local actors have been less likely to invest public resources in deprived areas (Williams and Collins, 2001). Greening, therefore, is considered a promising strategy to reduce violence-related disparities (South et al., 2021).

Tree canopy is a specific dimension of greenness that appears to reduce firearm violence. In Philadelphia, PA, a case-control and case-crossover study of injured youth and community controls found that time spent under tree canopy was associated with reduced risk of firearm injury (Kondo et al., 2017a). Tree planting in Portland, OR, was associated with reductions in violent crime (Burley, 2018). At the neighborhood level, a study from Cincinnati, OH, found that tree canopy loss from a large-scale pest infestation was associated with increased violence (Kondo et al., 2017b). Studies from individual cities have also found cross-sectional associations between neighborhood tree cover and lower crime and violence (Shepley et al., 2019). Possible explanations include the stress reduction associated with exposure to greenness, which might prevent disputes from escalating into violence. Alternative mechanisms include the heat-mitigating effect of urban tree canopy (Ziter et al., 2019), which may dampen aggression (Anderson, 1989); or the possibility that greener neighborhoods encourage residents to engage positively, creating social ties and collective action that deters aggressive behavior (Heinze et al., 2018).

Equalizing neighborhood-level access to tree canopy is the focus of the growing movement for “tree equity.” (Leets et al., 2022) Advocacy groups have proposed ambitious targets to increase urban tree cover, particularly in socially deprived areas. It remains unknown, however, whether these efforts might help address racial disparities in firearm violence exposure. The current study examined this question. Since developing tree canopy is a long-term process, experimental approaches were not practicable. Instead, we used cross-sectional analysis and simulations to describe plausible outcomes under hypothetical scenarios (Keyes et al., 2022). We used census tract data on segregation by race and income, proportion tree cover, and firearm violence from six mid-Atlantic U.S. cities, from 2015 to 2020. This study had two goals: to (a) test the associations of segregation and tree canopy with firearm violence, and (b) simulate the possible effects of proposed tree canopy targets on firearm violence, particularly in the neighborhoods most disadvantaged by segregation.

## 2. Data and methods

### 2.1. Data

For this cross-sectional analysis, the units were census tracts. To measure proportion tree cover, we used high-resolution (1 m) land cover data generated by the Chesapeake Conservancy from 2013 to 2014 aerial imagery, following commonly standards for land cover classification (Land Cover Data Project 2013/2014 - Chesapeake Conservancy, 2022). Every pixel was classified as tree canopy, structure, water, *etc.* We aggregated pixel categories by census tract then calculated tree canopy cover as the proportion of total land pixels that were tree canopy. Supplemental Fig. 1. Pixel categories distinguished tree canopy—our study measure—from shrubbery and low vegetation, which may increase crime by obscuring sight lines.

We measured racialized economic segregation using the index of concentration at the extremes for race and poverty (hereafter “ICE”), using 5-year census tract data from the American Community Survey (ACS). We used 2015–2019 ACS data, to coincide with the period of study outcomes. ICE is calculated as the number of White-headed households with high incomes (\$100,000/year or more) minus the number of Black-headed households

with poverty-level incomes, divided by total households. An ICE score closer to  $-1$  reflects greater deprivation, while a score closer to  $1$  reflects greater privilege. An advantage of the ICE measure, compared to commonly-used measures of concentrated disadvantage, is that it encodes not only disadvantage but also privilege: two neighborhoods with relatively low disadvantage might vary substantially in the extent to which residents can use wealth to advance their objectives (Feldman et al., 2015). Few prior studies have used the race-income ICE to analyze firearm violence outcomes (Krieger et al., 2017; Schleimer et al., 2022). One found that the race-income ICE outperformed other commonly-used segregation indicators in predicting firearm violence (Krieger et al., 2017).

Outcomes were aggregated 2015–2020 counts of fatal and non-fatal shooting incidents from the Gun Violence Archive (GVA), a nonprofit organization that collects reports of shootings from public records (Gun Violence Archive, 2021). Suicides and suicide attempts are excluded. Unlike data from government agencies, which are typically only available by city or county, GVA data include more precise locations, enabling neighborhood-level analyses. Some work has found that GVA firearm homicide yearly total align closely with federal estimates (Rochford et al., 2021); other work has found gaps in GVA data (Kaufman et al., 2020). To our knowledge, no study has attempted to validate neighborhood-level counts of GVA incidents, *i.e.*, our outcome measure. Thus, as a preliminary analysis, we obtained police data from Philadelphia (Shooting Victims - Datasets - OpenDataPhilly, 2022) and compared census tract shootings counts in GVA and in Philadelphia police data from the same time period.

We included covariates for other possible confounders for each census tract. Built environment covariates were the land area of the tract and location counts for nine categories of social and commercial activity locations: barber shops, bars, beauty salons, convenience stores, liquor stores, pharmacies, places of worship, restaurants, and schools (Jay, 2020a). These locations were 2014 tract-level counts obtained from ReferenceUSA. The specific types were selected based partly on documented spatial associations with firearm violence (*e.g.*, liquor stores (Jay, 2020a), schools (Barboza, 2018)) and partly on high frequency in the database for the study locations, suggesting their relevance as markers of social and commercial activity. Social environment covariates were obtained from the 2015–2019 ACS and included total population, median age, unemployment rate, low education rate (adults over 25 with education below high school level), and housing vacancy rate (Wood, 2003).

## 2.2. Analyses

We calculated descriptive statistics for the study variables by city. We omitted census tracts for which ICE could not be calculated (*e.g.*, had zero households for which income information available) and for tracts with population under 500. Since no prior work, to our knowledge, has evaluated the relationship between tree cover and ICE, we plotted these variables and calculated correlation coefficients ( $\rho$ ) for each city.

Next, we used statistical models to estimate shootings as a function of ICE and tree cover (Goldstick et al., 2015; Elliott Goldstick et al., 2015). Since shootings were overdispersed, right-skewed counts, all models were quasi-Poisson regressions. We included logged, tract-level population as an offset. Instead of Akaike's information criterion (AIC), quasi-Poisson

regression requires quasi-AIC for model comparisons. Covariate controls were selected with a backwards stepwise process, using quasi-AIC to assess for fit. We retained tract area, and counts of barber shops, beauty salons, places of worship, liquor stores, unemployment, low education, and vacancy rate.

To enable direct comparison of effect sizes, we rescaled independent variables by standard deviation (SD) and centered at the mean value. Our main models combined data from all cities and included a fixed effect for each city; we conducted secondary analyses separately for each city. We ran the model with and without adjustment for covariates. Estimates were calculated as incident rate ratios (IRR).

Instead of implementing these quasi-Poisson regressions as generalized linear models, we used generalized additive models (GAMs). GAMs are a more flexible alternative that enabled us to use smoothing splines to address spatial dependence. Each model included a thin plate regression spline over the X-Y coordinates of each census tract centroid. These splines were smooth, 2-dimensional spatial surfaces fit non-parametrically alongside the other covariates. The smoothness of the splines was determined automatically by generalized cross-validation (Wood, 2003). We implemented the fitting procedure with the R package *mgcv* using default GAM settings and the “bs = ts” option to select the thin plate spline (Wood, 2003).

The purpose of these splines was to absorb unmeasured spatial confounders that could have biased model estimates. Theoretically, confounders included contagion effects from nearby violence and spill-over effects from social disadvantage in nearby areas; compared to traditional approaches such as spatial lag regression, using thin plate splines involved fewer assumptions about the nature of these spatial dynamics (*e.g.*, whether to define spatial relations based on distance *vs.* contiguity). This approach has been used in prior injury research (Goldstick et al., 2015; Elliott Goldstick et al., 2015; Jay, 2020b); more broadly, splines are commonly used to address possible confounders (*e.g.*, from seasonality or long-term trends when estimating policy effects over time) (Bhaskaran et al., 2013). To test for residual spatial dependence, we calculated a Global Moran’s I among residuals from each model.

To specify the predictive model for our simulation analysis, we tested for non-linearities in the main exposures and interactions between them. For the resulting model with the lowest quasi-AIC, we assessed predictive performance by calculating out-of-sample R-squared across 10,000 iterations of 10-fold cross-validation.

We used the best-performing regression model to predict possible changes in shootings under hypothetical scenarios in which tree cover changed. Tree cover scenarios were based on a truncated version of the Tree Equity Score methodology proposed by the organization American Forests (Tree Equity Score Methodology, 2022). This methodology assigns a density-adjusted canopy target based on (a) a baseline target corresponding to a city’s natural biome (*i.e.*, forest, grassland, or desert); and (b) an adjustment factor based on population density, since higher-density areas have less room for trees. All cities in our study had forest biomes and therefore a 40% baseline tree canopy target. One rationale for this

40% target is that it may be a threshold at which urban heat islands dissipate (Ziter et al., 2019). Given this baseline target, the density-adjusted tree cover targets ranged from 0.20 to 0.48.

In our simulations, we tested baseline tree canopy targets ranging from 1% to 50%, including the 40% Tree Equity Score target, with population density adjustment. For each scenario, we simulated tree equity by replacing observed tree cover values with the target value for every census tract where the observed value fell below that target. We re-estimated the model with the new data and compared the predicted outcomes to our observed 2015–2020 outcomes. In each scenario, we assumed no change in ICE or any other variable. We analyzed the results by ICE quintile to compare impacts across levels of deprivation/privilege.

The Boston University Institutional Review Board waived review of this study as non-human subjects research, since all data were publicly available. All analyses were conducted in R (Team RC, 2013). Models were implemented using the *mgcv* package (Wood, 2012).

### 3. Results

City population ranged from 76,000 in Wilmington to over 1.5 million in Philadelphia. Wilmington displayed the highest average deprivation on the ICE measure (population-weighted mean =  $-0.14$ ). Washington displayed the highest average privilege (0.10). Annual *per capita* shootings rates were highest in Wilmington (population-weighted mean = 156.0 per 100,000) and lowest in Syracuse (57.5 per 100,000 residents). Among the six cities, average tree cover by census tract was highest in Syracuse (0.31) and lowest in Philadelphia (0.19). Table 1.

We found 15,235 total shootings over the study period. In Philadelphia, census tract counts of shootings in the GVA data correlated at  $\rho = 0.98$  with Philadelphia police data, supporting the use of GVA data. Supplemental Fig. 2.

Although tree cover varied considerably in relation to ICE scores, it was weakly positively associated with ICE scores (*i.e.*, greater privilege) in each city. This association was strongest in Wilmington ( $\rho = 0.36$ ) and weakest in Washington, where the Pearson correlation was close to zero ( $\rho = 0.02$ ). Fig. 1.

Our unadjusted model contained a spatial smooth and city fixed effects, but no built or social environmental covariates. In this model, a 1-SD increase in ICE was associated with a 54% reduction in firearm violence (IRR = 0.46, 95% CI [0.44, 0.49],  $p < 0.001$ ). Table 2. The association was similar when we adjusted for built environment covariates. When we also adjusted for social environment covariates, the estimated reduction was 42% (IRR = 0.58, 95% CI [0.54, 0.62],  $p < 0.001$ ).

In the unadjusted model, a 1-SD increase in tree cover was associated with a 21% reduction in shootings (IRR = 0.79, 95% CI [0.73, 0.84],  $p < 0.001$ ). When we added built environment covariates, we found a 16% reduction in firearm violence (IRR = 0.84,

95% CI [0.79, 0.90],  $p < 0.001$ ). When we further added social environment covariates, the estimated reduction was 9% (IRR = 0.91, 95% CI [0.86, 0.97],  $p = 0.005$ ).

Global Moran's I tests found no spatial autocorrelation in the residuals of the fully-adjusted model. Adding an ICE-tree cover interaction did not improve the model's quasi-AIC, nor did adding non-linearities in tree cover. The best-performing model included a natural spline of degree 4 on the ICE variable, suggesting non-linearity in the association between ICE and firearm violence. Supplemental Fig. 3.

In prediction tests using 10-fold cross-validation, this model explained the majority of out-of-sample variance: mean R-squared over 10,000 iterations model was 0.77 (SD = 0.05), versus 0.76 (SD = 0.05) for the linear exposure model.

When we simulated the effect of achieving the Tree Equity Score targets (*i.e.*, 40% minimum tree cover, before population density adjustment), reductions in firearm violence disproportionately benefited the most deprived census tracts. In the most-deprived quintile, average shootings per census tract declined by 3.3 shootings, compared to a 0.3 shooting decline in the most-privileged quintile. Fig. 2. In higher-deprivation quintiles, lower tree cover targets (*e.g.*, 30%) also yielded non-trivial reductions. However, even after achieving the 40% Tree Equity Score target, simulated shootings in the most-deprived quintile were still greater than the shootings observed in the second most-deprived quintile, prior to any change in tree cover.

#### 4. Discussion

In this cross-sectional study, we found that neighborhood-level segregation, as measured by ICE for race-income, was strongly associated with firearm violence. Higher neighborhood tree cover was associated higher ICE scores (*i.e.*, greater privilege) and with lower rates of firearm violence. However, ICE was a stronger predictor of firearm violence than was tree cover, particularly after adjusting for built and social environmental conditions. In our simulation, we found that achieving universal targets for tree cover was associated with non-trivial predicted reductions in firearm violence. These predicted reductions were greatest in the most-deprived neighborhoods, though these changes did not overcome the larger, baseline differences associated with segregation.

Our findings underscore structural deprivation and privilege as root causes of firearm violence. Compared to an average neighborhood, we found that each 1-SD increase in structural privilege on the ICE measure was associated with 42% lower firearm violence rates in our fully-adjusted model. The even larger estimate, of a 53–54% reduction in our simpler models, may provide a more accurate indication of the influence of segregation, since differences in neighborhood-level conditions (*e.g.*, educational and employment opportunities) lie on the causal pathway between segregation and firearm violence. ICE may be the single strongest predictor of community firearm violence (Krieger et al., 2017), as it is meant to capture the most important axes along which social stratification and spatial polarization are imposed. Another recent study highlighted the extent to which racialized economic segregation structures firearm violence risk, finding that the pandemic-related

surge in violence was concentrated in the neighborhoods displaying the greatest deprivation on the race-income ICE (Schleimer et al., 2022).

We also identified an association between neighborhood tree cover and firearm violence across six cities. To our knowledge, no prior work has examined cross-sectional associations between tree cover and violence on this spatial scale. In our fully-adjusted model, a 1-SD increase in tree cover was associated with a 9% reduction in firearm violence, conditional on racialized economic segregation, other built and social environment variables, city fixed effects, and a regression spline designed to absorb spatially patterned confounders (Kondo et al., 2017a; Burley, 2018; Kondo et al., 2017b). We found this association at the level of census tracts, indicating that neighborhoods are an important spatial scale at which to understand the effect of tree canopy. We found no interaction between tree cover and segregation—*i.e.*, ICE did not modify the tree cover-firearm violence association—nor non-linearities in the tree cover-firearm violence association.

The diminution of the estimated association, when controlling for built and social environment, suggests that some of the bivariate relationship between low tree cover and firearm violence is explained by other factors. For instance, tree cover may be crowded out by commercial activity, which generally facilitates the interpersonal interactions that lead to violence (Browning et al., 2010). Property vacancy may result in tree canopy loss due to disinvestment, but also contributes to firearm violence *via* fear and physical disorder (Garvin et al., 2013). Future work should further examine these possible mechanisms.

Contrary to our expectations, tree cover was not strongly associated with ICE across all cities. Some prior work has also found weak or null associations between segregation and tree cover, particularly after accounting for spatial dependence, as our models did (Duncan et al., 2014, Wolch et al., 2014). One possible explanation is that rapid, recent gentrification in study cities, particularly Washington (Jackson, 2015), may have partially decoupled segregation from tree cover, with changes in tree cover coming more slowly than changes in demographic composition. Another is that high-privilege neighborhoods may display low tree cover because tree canopy is sacrificed in those locations for other amenities, such as higher density of shopping or transit (Donovan et al., 2021), as indicated by the relatively high frequency of high-privilege tracts at the bottom of the tree cover distribution in Fig. 1. In turn, if tree cover is traded for other amenities that attract pedestrians, firearm violence might not increase, since pedestrians provide “eyes on the street” (Jacobs, 1961) to deter violence. To account for this possible source of confounding, we included other built environment covariates in our adjusted models.

While our models are cross-sectional and therefore cannot be used to determine causal relationships, our simulation modeling results indicate that increasing tree cover could reduce firearm violence at high levels of structural deprivation. This finding is consistent with results from a randomized greening experiment, in which the largest firearm violence reductions were observed in the highest-poverty neighborhoods (Branas et al., 2018). Benefits from increasing tree cover could focus even more closely on the most-deprived communities by assigning them priority in tree-planting efforts, a strategy advocated by tree equity proponents.



Changes to tree cover alone, however, appear unlikely to eliminate racial disparities in firearm violence exposure. Even when tree equity targets were achieved in our simulation, we estimated sizeable gaps in firearm violence across ICE quintiles. Investments in the built environment must be accompanied by major, long-term investments to reverse inequities in educational and employment opportunity, community trauma, police violence exposure, and other dimensions of structural racism. Moreover, one troubling finding from prior work is that increases in tree cover may be accompanied by gentrification and the displacement of low-income residents (Donovan et al., 2021). This dynamic could increase, not reduce, inequities in exposure to tree cover and firearm violence. One possible advantage of municipal and regional tree equity plans is that simultaneously increasing greenness across many neighborhoods could help buffer gentrification effects. However, more deliberate anti-displacement programs could further limit the potential for gentrification. Moreover, healthy tree canopy requires cities to devote resources not only to tree planting but to tree maintenance, fallen leaf removal, and other services, including in neighborhoods that are traditionally underserved. Community-engaged services are vital to making spaces “just green enough” to deliver benefits, without accelerating gentrification (Wolch et al., 2014).

#### 4.1. Limitations

Because this study was cross-sectional, we are not able to infer causation. Unmeasured confounders could potentially explain the relationships among ICE, tree cover, and firearm violence. However, we included population, and tested 15 built and social environment indicators as covariates, and we used thin plate regression splines to account for any spatially-patterned potential confounders, which eliminated residual spatial autocorrelation.

We derived firearm injury outcome measures from GVA data, which are not official government records and could be biased by the types of incidents that appear in local news stories. While we validated data for one city (Philadelphia) against GVA data and found high correlation ( $\rho = 0.98$ ), additional work is needed to validate GVA over time and space.

Finally, our simulations were based on numerous assumptions that simplified the analysis. For example, we assumed that no other covariates would change as tree cover increased, even though major changes in tree cover could be accompanied by changes in population and/or sociodemographic composition. Moreover, declines in firearm violence could be self-reinforcing over time, as the influence of retaliation and violence exposure weaken. We also did not examine risk for individuals. Future computer simulation work, *e.g.*, using agent-based modeling, could address these complex, dynamic processes (Goldstick and Jay, 2022).

## 5. Conclusions

Firearm violence prevention is not often cited as a rationale for increasing tree cover and advancing tree equity. However, we found that increasing tree cover has the potential to reduce firearm violence, particularly in the most-deprived neighborhoods. According to our results, advancing tree equity would not disrupt the fundamental causes of racial disparities in exposure to firearm violence, but could nonetheless help to mitigate those disparities.

These findings suggest important alignment between the goals of tree equity and firearm violence prevention.

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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## Data availability

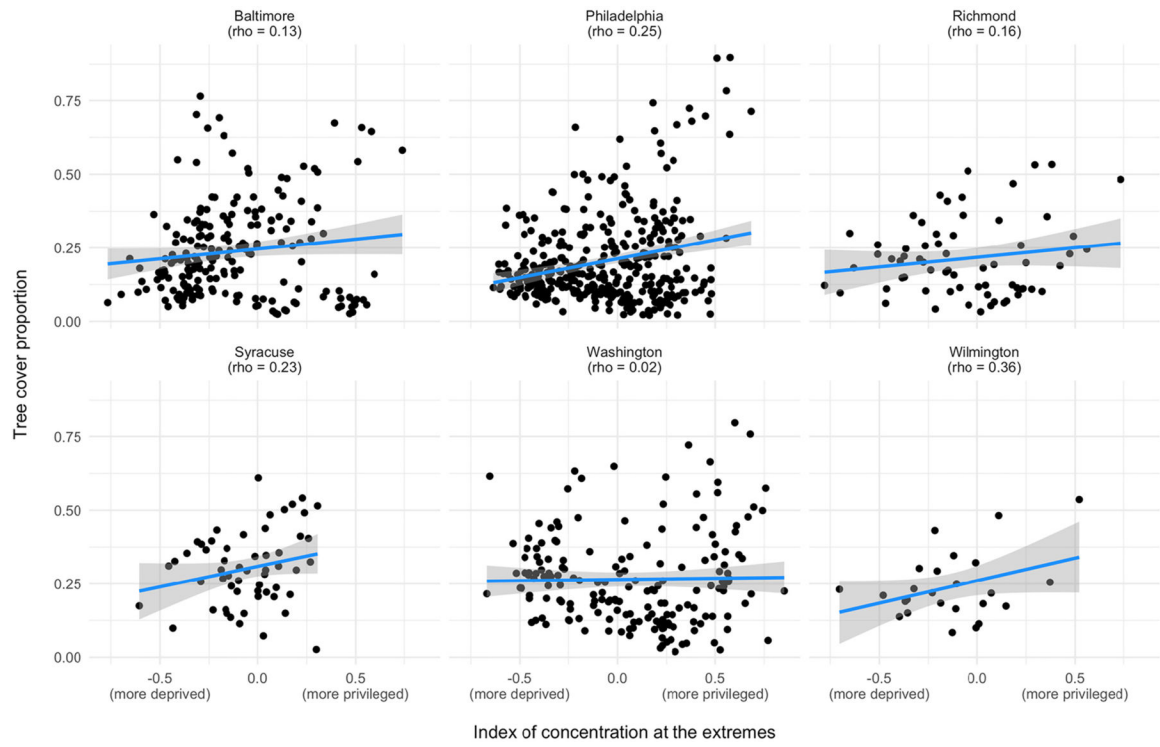
Data will be made available on request.

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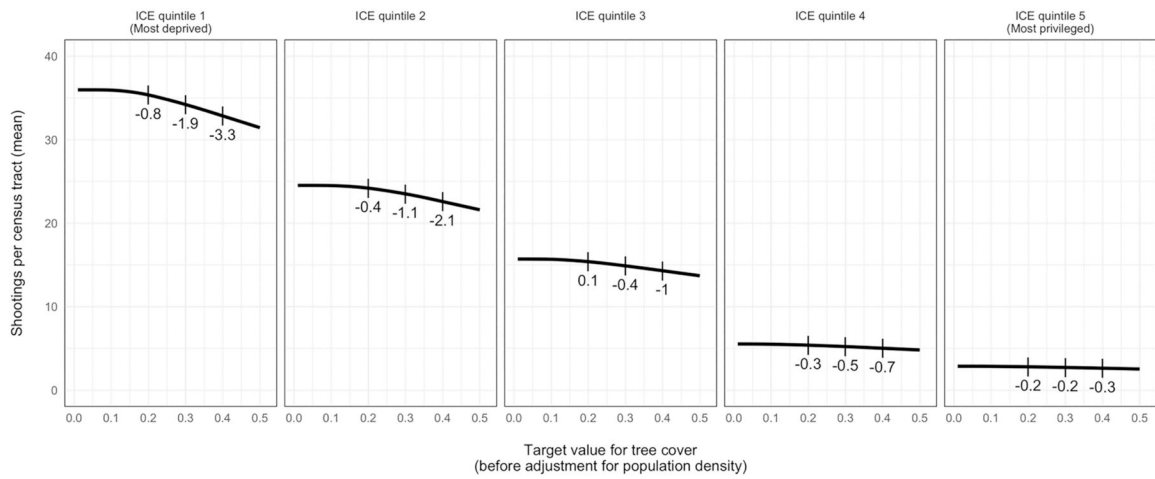
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**Fig. 1.** Bivariate association between tree cover and index of concentration at the extremes for race-income.

*Note.* Rho is the Pearson correlation coefficient, calculated separately for each city.



**Fig. 2.**

Predicted firearm violence outcomes by ICE quintile, under simulated proportion tree cover scenarios.

*Note.* Labeled outcomes represent the mean reduction in shootings at each tree cover target value, calculated at the census tract level. For each tree cover target value, census tracts with tree cover below the target value were adjusted upward to that value. The target value was adjusted according to population density, using a formula described in Methods.

**Table 1**

Characteristics of census tracts in study sample, by city.

City	Total population (1000s)	N census tracts <sup>a</sup>	Census tract mean				
			Population	Street length <sup>b</sup>	ICE <sup>b</sup>	Tree cover <sup>b</sup>	Shootings rate per 100k <sup>b</sup>
Philadelphia, PA	1567	375	4179	11,529	-0.07	0.19	60.7
Washington, DC	669	178	3757	10,869	0.10	0.27	63.1
Baltimore, MD	616	198	3109	12,265	-0.11	0.26	126.1
Richmond, VA	221	66	3347	26,731	-0.08	0.24	85
Syracuse, NY	147	56	2626	14,906	-0.04	0.31	57.5
Wilmington, DE	76	25	3035	13,756	-0.14	0.25	156

*Notes.* Population and demographic data were obtained from the American Community Survey, 2015–2019 5-year estimates. Street length was obtained from calculations using OpenStreetMap (Boeing, 2019). We calculated proportion tree cover using 1 m land cover classification data generated by the Chesapeake Conservancy, from 2013 to 2014 NAIP imagery (Land Cover Data Project 2013/2014 - Chesapeake Conservancy, 2022). Shootings were 2015–2020 fatal and non-fatal incidents obtained from the Gun Violence Archive (Gun Violence Archive, 2021).

<sup>a</sup>Omits census tracts for which ICE estimates could not be calculated.

<sup>b</sup>Weighted by census tract population.

**Table 2**

Results of quasi-Poisson regression models analyzing linear associations of segregation and tree cover with firearm violence.

Exposure variable (scaled by std. dev.)	Model 1 (main exposures only)			Model 2 (built environment added)			Model 3 (social environment added)		
	IRR	95% CI	p	IRR	95% CI	p	IRR	95% CI	p
ICE for race-income (higher = more privilege)	0.46	0.44, 0.49	< 0.001	0.47	0.44, 0.50	< 0.001	0.58	0.54, 0.62	< 0.001
Tree canopy cover	0.79	0.73, 0.84	< 0.001	0.84	0.79, 0.90	< 0.001	0.91	0.86, 0.97	0.005
Tract area				0.92	0.87, 0.97	0.001	0.93	0.89, 0.97	0.002
Barber shops				1.05	1.01, 1.09	0.02	1.05	1.02, 1.09	0.004
Beauty salons				1.00	0.95, 1.05	0.94	1.05	1.01, 1.09	0.03
Places of worship				1.12	1.08, 1.17	< 0.001	1.08	1.05, 1.12	< 0.001
Liquor stores				1.09	1.05, 1.13	< 0.001	1.07	1.03, 1.10	< 0.001
Unemployment rate							1.05	1.00, 1.09	0.03
Vacancy rate							1.23	1.18, 1.28	< 0.001
Low educational attainment							1.23	1.18, 1.29	< 0.001

*Notes.* Exposure variables were centered at the mean value and scaled by one standard deviation for comparability, then modeled as linear predictors. Models were quasi-Poisson regressions that included a lagged population offset, a fixed effect for each city, and controlled for street segment length and counts of barber shops, beauty salons, places of worship, liquor stores, convenience stores, and schools. Models also included thin plate spline terms (degrees of freedom = 29) to account for unmeasured spatial confounding. (Goldstick et al., 2015)