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Shootings and land use

Alex Knorre *, John MacDonald

Department of Criminology, University of Pennsylvania, United States of America

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ABSTRACT

Purpose: To test whether land use and other features of places are associated with the spatial concentration of gun violence or its growth during epidemic periods.

Methods: The study uses shooting data from six major cities over a four-year period (2018–2021). Regression models with spatial lags estimate whether the land use of places is associated with differences in shooting rates and the surge in shootings that occurred in 2020–2021.

Results: Mixed-land use is associated with lower rates of shootings overall, but land use has little relationship with the surge in shootings in 2020–2021. The most disadvantaged areas consistently have higher rates of shootings. The change in shooting rates is multiplicative, such that areas of concentrated disadvantage faced the highest absolute rate change in shootings in 2020–2021.

Conclusions: This study underscores the importance of social disadvantage in explaining the enduring and episodic rates of gun violence.

1. Introduction

After over a decade of historically low rates of gun violence in the United States, gun homicides increased by nearly 25% in 2020 ("Shootings never stopped during the pandemic", 2021). While the change in gun homicide rates varied in magnitude across major cities, the majority of cities experienced increases in gun violence (Sutherland, McKenney, & Elkbuli, 2021). Philadelphia, for example, experienced a 45% increase in shootings between 2019 and 2020. The reasons for the rise in gun violence in US cities in 2020 remains a bit of a puzzle, as shutdowns, social distancing, and other disruptions in routine activities caused by the COVID-19 pandemic were generally associated with lower overall levels of total crime (Abrams, 2021). At the same time, crime rates are higher during the pandemic if one uses estimates of the number of active people on the street as the denominator (Massenkoff & Chalfin, 2022). These findings suggest that the pandemic-related shift in routine activities affected the patterns of shootings differently than the general crime rates.

Gun violence is clustered in time and space more than the general concentration of crime (Weisburd, 2015). For example, in Boston over a 29-year period, only 11.5% of street segments accounted for all of the shootings (Braga, Papachristos, & Hureau, 2010). Research also suggests that the spatial concentration in shootings is relatively stable over time, with only minimal evidence of spatial diffusion, and occurs disproportionately in the most socially disadvantaged places (Braga et al., 2010; Brantingham, Carter, MacDonald, Melde, & Mohler, 2021; Cohen & Tita, 1999; Griffiths & Chavez, 2004; Morenoff, Sampson, & Raudenbush, 2001; Ratcliffe & Rengert, 2008).

There are two dominant explanations for the spatial concentration of crime that also apply to shootings. One perspective focuses on social ecological factors, like concentrated disadvantage, that are thought to influence the spatial patterns of crime by influencing differences in the levels of informal social controls between places (Morenoff et al., 2001). Another perspective emphasizes how the built environment of places (e.g., zoning codes, street configurations, type and quality of housing, and land uses) shapes criminal activity (MacDonald, 2015). These are complementary perspectives, one emphasizing the social aspects of community life, while the other examines how the built environment shapes opportunities for crime, neighborly interactions, and guardianship. Over the past decade, scholars have sought to combine these perspectives by examining how the social and physical environment of places influences the spatial patterns of crime and victimization between neighborhoods, street segments, and other spatial units (Browning et al., 2010; Kinney, Brantingham, Wuschke, Kirk, & Brantingham, 2008; Lee, O, & Eck, 2021; O'Brien, Ciomek, & Tucker, 2021; Stucky & Ottensmann, 2009). There is also a growing literature examining how the features of the social and built environment are associated with higher rates of gun violence (Beard et al., 2017; Schleimer et al., 2022),

* Corresponding author at: 558 McNeil Building, 3718 Locust Walk, Philadelphia, PA 19104-6286, United States of America.
E-mail address: a.v.knorre@gmail.com (A. Knorre).

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including historical effects of segregation and discrimination in real estate loans (Jacoby, Dong, Beard, Wiebe, & Morrison, 2018).

We are not aware of any recent studies that have comprehensively examined the relationship between land use, socioeconomic factors, and gun violence and how these associations are affected by the surge in shootings that occurred in the 2020–2021 pandemic. In this paper, we seek to fill a gap in the literature by examining how the physical and socioeconomic contexts of neighborhoods are associated with relative differences in shooting rates before and during the 2020–2021 increase in gun violence. We combine comprehensive measures of land use zoning, street networks, census population features of places, and shootings across six large U.S. cities (Baltimore, MD; Chicago, IL; New York, NY; Los Angeles, CA; Philadelphia, PA; Washington, DC). We create a hexagonal grid of each city and model the shooting counts between the years 2018 and 2021. We use spatially-lagged Poisson regression models to estimate the differences in shootings per area (hexagon) with a rich set of variables that measure land uses, street network connectivity, and several socioeconomic features. We use seemingly unrelated regression to assess whether the correlates of shooting rates changed before (2018–2019) and during (2020−2021) the pandemic rise in shootings.

This paper makes several contributions to our understanding of the spatial dynamics of gun violence. First, we rely on flexible models that allow us to examine the association between five types of land uses (residential, commercial, public facilities, industrial, and open space) and shootings. Second, we employ a localized measure of the effect of mixed land use that adjusts for spatially adjacent areas. Third, we rely on a hexagonal grid and spatial imputation of census population data, which allows us to compare estimates across six cities with a spatial approximation. As a result of these methodological contributions, we are able to more concretely examine how the land use and socioeconomic characteristics of areas are associated with the enduring and epidemic rise in gun violence across six major U.S. cities.

We find that the shootings occur at a greater rate among areas with a high percentage of residential and commercial zoned buildings. By contrast, in the majority of cities mixed land uses relative to adjacent areas are associated with fewer shootings. The higher density of street intersections is associated with a higher rate of shootings in five out of six cities. Higher levels of concentrated economic disadvantage in areas are associated with more shootings in all six cities. The surge in shootings in 2020–2021 was only slightly more pronounced in the areas with a high degree of concentrated disadvantage from a statistical sense, but the absolute change in shooting rates means that areas of concentrated disadvantage faced substantially more shootings during the pandemic rise in gun violence.

2. Background

Today, the theory of social disorganization provides the dominant framework for explaining why crime tends to concentrate in specific areas of cities. From this perspective, crime occurs in places that exhibit indicators of concentrated disadvantage, measured by greater levels of poverty, unemployment, public assistance, incarceration, and racial segregation (Chamberlain & Hipp, 2015; Sampson, 2021; Weisburd, Groff, & Yang, 2012). According to social disorganization theory, concentrated disadvantage influences the ability of neighborhoods to exercise effective informal social controls in places to prevent crime (Sampson, 2008). Specifically, the hyper-concentration of multiple forms of poverty disables neighborhood networks through a variety of channels, including making it more difficult for residents to monitor youth, engage in activities of mutual trust, and overall establish a sense of collective efficacy to enforce social norms (Morenoff et al., 2001; Sampson, 2008). Once patterns of crime and violence become endemic, it further destabilizes communities, leading to business disinvestment, population decline, and a greater relative increase in the concentration of poverty (Sampson, 2021; Skogan, 1990). Endemic differences in violence are also thought to bring a shift in norms to the street, as community members have to learn to navigate the streets and project a tough image to prevent themselves from becoming a victim (Anderson, 2000). Additionally, persistent community violence leads to the diminishing effects of state-supported crime control through deteriorating trust in the police and increasing legal cynicism (Kirk & Papachristos, 2011). Thus, growing up in areas where violence becomes a socially acceptable response to simple insults or other affronts is a powerful driver of the spatial patterns of violence. A surge in gun violence may also be more likely when violence becomes a normal response to an affront and a subset of the population is carrying firearms (Braga, Griffiths, Sheppard, & Douglas, 2021).

At the same time, some studies stress the importance of the spatial dimension of offending and focus on the effects of the physical features of the built environment (Hipp & Williams, 2020). Several interconnected theories such as rational choice, routine activity, and crime pattern theory argue that the built environment of places (e.g., facilities such as schools, taverns, convenience stores, churches, apartment buildings, and public housing projects) shapes the spatial patterns of crime by attracting more potential victims and offenders (MacDonald, 2015; Wilcox & Cullen, 2018). Crime tends to cluster around places with more environmental features that make offending easier (Eck & Weisburd, 2015). Environmental factors conducive to crime include places with a high concentration of cash, such as liquor stores, bars, fast-food restaurants, and pawn shops, which in turn produce opportunities for robberies. Crime pattern theory notes the importance of places that are easily accessible to the public where a large number of people concentrate (crime generators), and where there are opportunities that make crime more attractive (crime attractors) (Wilcox & Cullen, 2018). Transportation centers, road networks, and other places that draw more people are generally thought of as generators of crime; whereas bars, taverns, and places where people are exchanging cash are more likely to be attractive places for would-be offenders looking for robbery victims (Bernasco & Block, 2011; Jean, 2007). Taken together, these factors contribute to the social and environmental context through which crime occurs (Brantingham & Brantingham, 1995).

The configuration of streets is among the physical features of the urban landscape that shapes the crime environment, as more permeable streets may lead to fewer crimes by enabling more "eyes upon the street" and informal social controls. Davies and Johnson (2015) show that the street-level betweenness is a significant predictor of residential burglaries in Birmingham, UK. Kim and Hipp (2021) found that the density of business establishments and greater land use diversity was associated with more crime in Southern California, but that more interconnected streets were associated with fewer crimes. Frith, Johnson, and Fry (2017) also found that the risk of burglary is inversely dependent on the density of non-local traffic on the street. These findings suggest that street configuration may impact crime when it is situated in an environment that encourages more walking and neighborly interaction.

Easier street access to locations also might increase crime by bringing more potential offenders. Research has found that the lack of street connection is associated with fewer crimes when neighborhoods are located in areas of higher elevation (Kim & Wo, 2021), suggesting that the topography of places may also help shape the context in which street designs effects crime. Gun violence may operate differently from general crimes of opportunity, such that street density may make shootings more likely to occur if they are a result of gang rivalries. Operation "Cul De Sac" organized by the Los Angeles Police Department in the early 1990s found that installing traffic barriers on street in South Los Angeles decreased the incidence of drive-by shootings and assaults (Lasley, 1996). While the configuration of the street networks is relevant for the spatial modeling of crime, it is unclear how much street networks matter in explaining stability and change in patterns of gun violence.

Research has extensively examined the associations between the built environment and the spatial concentration of crime and violence, but there are fewer studies examining whether zoning and land use are associated with spatial patterns in gun violence.

Smith, Frazee, and Davison (2000) examined how robberies varied across street segments as predicted by the number of land use variables (e.g., hotels, stores, vacant lots, parking lots, multifamily residential buildings, commercial places, bars, and restaurants) and the social disadvantages of places (e.g., racial heterogeneity, single-parent families, and low-value buildings). They found that a number of land use variables were associated with higher counts of robberies on a street block, including a 9% increase for robberies with each hotel and a 5% increase for each bar or restaurant. Lockwood (2007) analyzed the correlations of rented residential, public, and commercial buildings with violent offenses in Savannah, GA, while controlling for concentrated disadvantage. The study found statistically significant associations between land use variables and violent crime. However, Lockwood (2007) measured land use by simply counting the number of polygons in each major category, which might result in a substantial measurement error (e.g., the average residential unit might be much smaller than an average public facility).

More recent studies of zoning and crime try to approximate spatial coverage of different land uses by using the percentage of each land use for a given spatial unit. In these studies non-residential land use tends to be positively associated with higher rates of crime (Lee et al., 2021). Browning et al. (2010) studied the effects of land use composition on violent crime in Columbus, OH. They model rates of homicides, aggravated assaults, and robberies across census tracts, and include percentages of commercial and residential parcels, disadvantage index, residential instability, and other socioeconomic measures. They found that the share of commercial and residential parcels per census tract is correlated with the number of violent offenses, but in a form of an inverted U-shape. When there are many or few commercial and residential buildings there will be fewer homicides and aggravated assaults. This suggests that the relationship between different types of land use and crime might be non-linear, such that it is important not to assume a linear functional form of the dependence.

Stucky and Ottensmann (2009) provide one of the most comprehensive studies to examine land use and crime that controls for a range of socioeconomic characteristics of places. Using a spatial regression model they estimated the number of violent offenses per area (square grid) as a function of land use (percentages of commercial, vacant, industrial, park, and water land use and availability of schools, hospitals, and cemeteries in each grid unit) and socioeconomic variables (population, ethnic composition, and disadvantage index). Stucky and Ottensmann (2009) found that the predicted number of violent offenses was higher in places with more commercial and high-density residential zones. The predicted number of violent offenses was by contrast substantially lower in depopulated industrial zones, water areas, and cemeteries. This study adds an important methodological innovation in spatial studies of crime by using a spatial raster of square grids instead of census-based spatial units. Census divisions differ in size based on population enumeration, and as a result have large heterogeneity in land uses. Census boundaries are also likely to suffer from the modifiable areal unit problem that is exacerbated in the case of crimes that are situated on streets at the edge of census geographies (for a complete discussion, see Appendix A in Stucky and Ottensmann (2009)).

Another recent study by O'Brien et al. (2021) analyzes whether the diversity in both land use and socioeconomic and ethnic composition of neighborhoods can explain the variance in the concentration of crime. Their study employs data on emergency dispatch calls to the police for public violence in Boston, MA, and connects these to city street segments. O'Brien et al. (2021) calculate a Gini index of inequality of crime concentration for census tracts in Boston, thereby estimating tract-level inequality in crime concentration across street segments. Using data on the land use along street segments, ethnic and socioeconomic composition from census data, and collective efficacy measures from the Boston Neighborhood Survey they found that land use diversity and ethnic and socioeconomic heterogeneity are the strongest predictors of higher concentration calls to the police related to public violence.

While a number of studies have examined land use patterns and violent crime, less research has examined comprehensive neighborhood-level measures of populations and land uses and the concentration of gun violence (see Johnson and Roman (2022)). Rather, studies of shootings typically focus on the temporal (in)stability and spatial concentration of shootings among places (MacDonald, Mohler, & Brantingham, 2022). Braga et al. (2010), for example, study firearm shootings with injuries among street units (segments and intersections) in Boston, MA over 1980–2008 and report that interpersonal gun violence is highly concentrated in a small number of places: only 11.5% of street units have experienced shootings at least once during 29 years, and only 0.8% have shootings each year. They also find that levels of gun violence at micro-places are stable over the years, and stress the importance of analyzing shootings at the smallest spatial resolution possible. Cohen and Tita (1999) analyze homicides in Pittsburgh, PA during the early 1990s and argue that diffusion of homicides happens only during peak years. Otherwise, the changes in homicide levels are sporadic (random) when they happen in non-adjacent neighborhoods.

Research also suggests that the spatial and temporal patterns in shootings are much smaller than conventional administrative boundaries, and tends to reflect patterns of endemic hot spots rather than spatial diffusion of gun violence (Loeffler & Flaxman, 2018). Other research has examined the space-time diffusion of shootings before and during the pandemic (Brantingham et al., 2021; MacDonald et al., 2022). Recently, Johnson and Roman (2022) find that the intensity of shootings in Philadelphia increased the most during the COVID-19 pandemic in racially disadvantaged neighborhoods with more active drug markets.

In general, the literature in criminology focuses more on examining the space-time concentration and stability of shootings and less on what social and physical features of places can explain this concentration and whether the association changes during an epidemic rise in gun violence.

3. Data and methods

We accessed the open data portals for each of the 100 most populated cities in the US and checked for those that had publicly available incident-level data on shootings that contained geographic coordinates (latitude and longitude) for multiple years. From these restrictions, we rely on the following six major U.S. cities with available data: Baltimore, MD; Chicago, IL; Los Angeles, CA; New York City, NY; Philadelphia, PA; and Washington, D·C.

For each of the six cities, we create an analytic data file containing counts of shootings, land use information, and socioeconomic characteristics within the same spatial reference grid of hexagons. The use of a spatial reference grid is a common approach that attempts to optimize on the smallest spatial resolution possible to capture aggregate social processes related to population, land use, and other features of the built environment correlated with crime patterns (Malleson, Steenbeek, & Andresen, 2019). For each city, we create a hexagonal grid with a side-to-side diameter of each hexagon of approximately 1000 ft (300 m), which is slightly larger than a standard street block. For example, a typical block in Chicago is 330 by 660 ft or 100 by 200 m. We overlay census block group shape files with the hexagon grids and remove the cells with no population, such as airports or water areas.

The use of the hexagon grids has several advantages over census block group boundaries with regard to the modifiable areal unit problem when it comes to scale and zoning effects (Fotheringham & Wong, 1991). First, census block groups scale in size to the residential population, creating significant heterogeneity that may violate the independence assumption required in a regression model. Second, land use and street network data are also likely to fall along census boundaries and created edge effects. Using the spatial grid partially solves these issues by imposing a uniform set of spatial units (Stucky & Ottensmann, 2009).

Third, the spatial grid also avoids problems with measurement errors in geocoding of data. For example, many police departments add artificial noise to the coordinates of offenses. The data manual for the Chicago shootings data explicitly states that “in order to preserve anonymity, the given coordinates are not the actual location of the crime,” but that they draw “a circle roughly the size of an average city block” and randomly pick a spot within that circle. Projecting shooting incidents onto unified hexagonal units results in smaller measurement errors than if we used census block groups whose shape and areas varies. Finally, the use of hexagonal units is superior to square/rectangular units because it results in smaller edge effects (Birch, Oom, & Beecham, 2007). Nevertheless, in using the hexagons for our analysis, we explicitly assume that the single hexagon size can be used across all six cities. We chose hexagons to be close to the size of a city block, but recognize other size hexagons may produce different results. However, we report the results from models using census block groups as an alternative spatial unit.

3.1. Dependent variable: Shootings

Our main dependent variable is measured by the sum of all shootings (lethal and nonlethal) that happened in 2018–2021. We are interested in the overall level of serious gun violence, and research suggests that the probability of the lethal outcome from shooting is largely driven by the caliber size of bullets (Braga & Cook, 2018) and the distance to the nearest trauma center (Hatten & Wolff, 2020).

We use publicly available data for all victim-involved shootings for Chicago, New York, and Philadelphia (Chicago Data Portal, 2021b; New York Police Department, 2021; OpenDataPhilly, 2021b). We use publicly available crime incident data for Baltimore, Los Angeles, and Washington D.C. and extract the shooting incidents (Baltimore City, 2021; Office of Los Angeles, 2021a, 2021b; Open Data DC, 2021b). For Los Angeles, we use the modus operandi (MO) code 0430 which stands for “victims shot” to extract shootings. For Baltimore, we use crime codes for firearm-related homicides or shootings (codes 1A and 9S in the CrimeCode variable with a gun as the indicated weapon). For the District of Columbia, we use the field that describes weapons as a method of offense in reported homicides and aggravated assaults.

Washington, D.C. and Baltimore, MD are less clear than the other cities on whether the gun-related assaults include threats and actual shootings. Neither city provides information on whether the victim was injured. Thus, the number of non-lethal shootings in these cities is higher than the number of people actually shot with a gun. The Baltimore data shows that for the year 2016, there were 271 fatal and 663 non-fatal shooting incidents, while the Giffords Center reports there were 275 fatal and 667 non-fatal shooting incidents in the same year (Giffords Law Center, 2018). For Washington, D.C. the data indicates 650–750 non-fatal gun assaults, while Metropolitan Police Department reports a figure of ~500 intentional gunshot injuries a year (Metropolitan Police Department, 2018, p.7). Therefore, we assume that D.C. captures a share of assaults with guns that do not result in an actual shooting.

We aggregate lethal and nonlethal shootings together, with lethal shootings accounting for approximately 20% of the total number of shootings in each city. Fig. 1 shows that the cities in our sample greatly vary in regard to the shooting rate per 100,000 residents. In 2019, New York City and Los Angeles had the lowest shooting rate at 11.7 and 23.8 respectively. Washington D.C. (shooting rate of 121.7), Philadelphia (shooting rate of 91), and Chicago (shooting rate of 97.8) were in the middle, while Baltimore had the highest shooting rate of 176.7. Fig. 1 shows that all cities aside from Baltimore experienced a major rise in shootings in 2020.

Shootings were aggregated to the total count in each hexagon for 2018–2021. and Fig. 2 shows the resulting grids for six cities. Additionally, we aggregate total counts separately for periods 2018–2019 and 2020–2021.

3.2. Independent variables: Land use and its diversity

To understand what types of urban landscapes are associated with more shootings, we access public data on land parcels for Chicago (535,178 parcels, Chicago Metropolitan Agency for Planning (2015)),

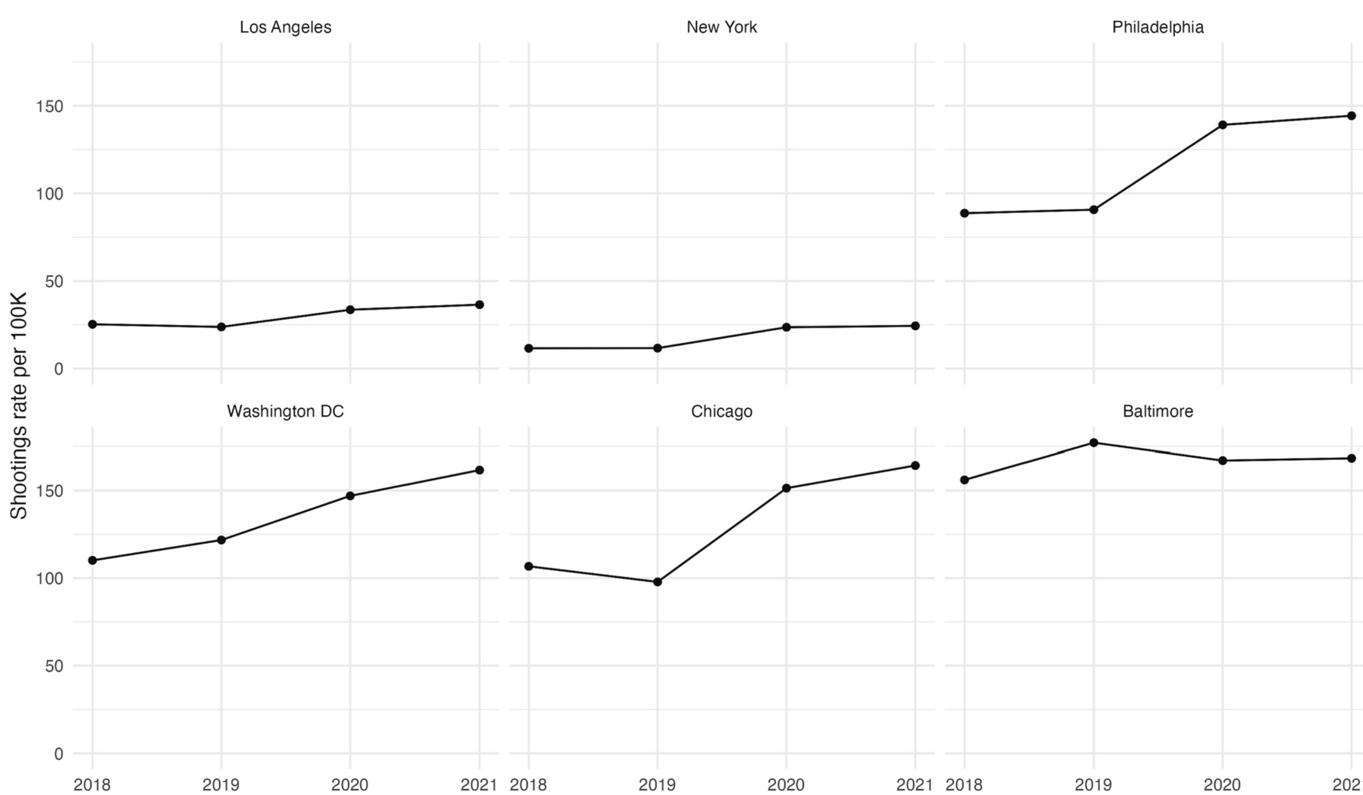

Fig. 1. Shooting rates in selected cities in 2018–2021.

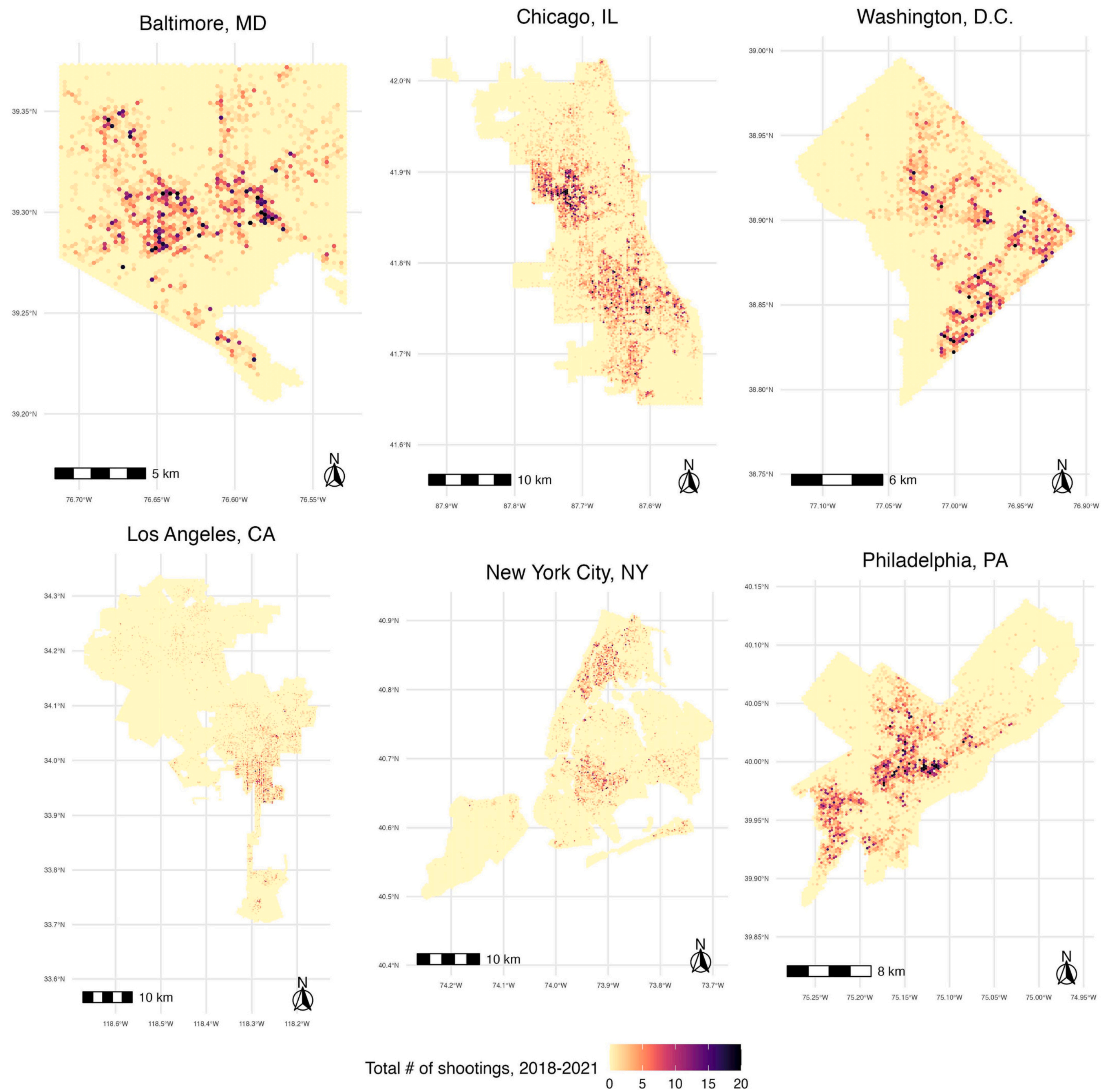

Fig. 2. The hexagonal grid with shootings in 2018–2021.

Los Angeles (53,127 parcels, Office of Los Angeles (2021c)), New York City (857,229 parcels, NYC Department of City Planning (2021)), and Philadelphia (560,104 parcels, OpenDataPhilly (2021a)). Baltimore, MD and Washington D.C. do not use land parcel data, so we rely on the zoning polygons, which leaves us with 1461 unique zones in Baltimore (Maryland Department of Planning, 2010) and 1194 zones in D.C (Open Data DC, 2021c).

We map each of the land use polygons (parcels or zoning codes) onto hexagonal grids. If a polygon crosses two or more hexagons, we divide the polygon and apportion its section to one hexagon only. We classify parcels and zoning codes into one of five land use classes: residential (all densities, single- and multi-family), commercial (all densities, including office buildings, shopping malls, retail, mixed with residential), industrial (including manufacturing, processing, mineral extraction, storage, and repair), public facilities (such as civic, cultural, institutional buildings, hotels, medical, educational, and religious facilities), and open space (parks and active recreation zones). We decided not to include parcels that are totally vacant or under construction, landfills, and water areas. We also remove transportation facilities and zones for streets, railroads, aircraft, and other communications, because we account for these attributes with street network connectivity measure. This exclusion also guards against a perfect collinearity problem, as the sum of all land use percentages would never reach 1. Given that one cannot assume a linear relationship between land uses and shootings, we categorize land uses into quantiles.

With many hundred thousand parcels and zones classified into one of five land use categories, we calculate how much area each of those categories occupies in each hexagon cell using percentages. For the subsequent modeling, we create percentile groups according to five percentage (quantiles) ranges of a hexagon captured by specific land use (0%; 1% to 10%; 10% to 25%; 25% to 50%; 50% to 100%). We chose to create percentile groups because of non-uniformity in land use percentages across areas. Additionally, using percentile groups instead of using the raw or squared percentage of the land use allows us to estimate a more flexible non-linear model of the relationships between land use and shootings. The various size of percentile groups follows the distribution of the most land use categories which are skewed to zero.

3.2.1. Land use diversity

To measure the diversity of land use, we use the Herfindahl–Hirschman Index (HHI), which was originally developed to measure the concentration of market share and later used to assess ethnic heterogeneity with the (inverted) Diversity Index (Rhoades, 1993). A measure of HHI close to zero means all five land use types occupying the same area in the cell. If the measure of HHI is close to one, it means the cell is dominated by a single land use. Here, we employ a modified HHI described by the following equation:

$$\mathrm{HHI} = \sum\nolimits_{i=1}^{n} (Relative\ landuse\ share_i)^2 \tag{1}$$

where *Relative landuse share* is the share of the land use i relative to the sum of all the land use percentages. We use the relative measure instead of the absolute one to deal with cases when the sum of land use shares is less than one. This happens when there are portions of land use, such as waterways and roads, that are not accounted for in these hexagons. We standardize the HHI measure by subtracting the average HHI in the adjacent 900 m (three times the diameter or 54 hexagon cells). This approach helps control for larger areal composition effects. For example, if a larger neighborhood is already diverse in terms of land use, we focus on the change in HHI for a specific hexagon compared to its adjacent neighbors. Thus, the resulting HHI measure is centered at 0; an HHI of 0 means that the land use concentration in the grid cell is no different from the local average. Land use concentration higher than 0 means that some land use types take disproportionately more space than others.

3.2.2. Street network connectivity

Street networks are a critical measure of the built environment that impacts patterns of human activity that are correlated with crime (Frith et al., 2017; Kim & Hipp, 2021). To control for this feature, we use the data on streets and their intersections in all six cities and estimate the measure of the average connectivity within each hexagon grid, relying on data prepared by Boeing (Boeing, 2018, 2019). Following Kim and Hipp (2021) for each street segment e within each hexagon cell we calculate its betweenness centrality:

$$B_e = \sum_{i,j \in V, i \sim 1} \frac{\sigma_{ij}(e)}{\sigma_{ij}} \tag{2}$$

where i and j are street segments, σ_{ij} is a number of all shortest paths between i and j, and $\sigma_{ij}(e)$ is a number of all shortest paths between i and j that go through e. Then, B_e estimates how central e is in the network. We also incorporate lengths of street segments as weights, so longer street segments have slightly more importance in the calculation of betweenness. Finally, we find the median betweenness centrality for each cell to measure the permeability of the street relative to adjacent streets, providing a proxy for the likelihood the street can be easily traveled through relative to nearby streets. We calculate the median instead of the mean because it is less sensitive to outliers within a hexagon.

3.3. Control variables: Socioeconomic characteristics

We include a range of socioeconomic variables using 5-year census block group estimates from the American Community Survey of 2019. These include the total residential population, median household income, the percent of the Black and Hispanic residential population, the share of residents living below the poverty line, the share of residents who recently moved, the percentage of homeowners, the unemployment rate, and the rate of single mothers per household. The data from census blocks were interpolated for each hexagon cell, as either the weighted sum for population counts or the weighted average for percentages and median income. We chose to use the cross-section of estimates from the ACS 2019 rather than a yearly panel of socioeconomic variables because the sampling error is too great to reliably detect year-to-year changes.

Because the percentages of Blacks, Hispanics, unemployment, poverty, single mothers, and median household income are highly correlated, we create the concentrated disadvantage index using principal component analysis (PCA). We also create a residential stability index using the percentage of recently moved residents and owner-occupied households. The factor loadings and the percentage of explained variance are listed in Table A.1 in Appendix. The PCA results show that cities have different associations between racial and ethnic minorities and concentrated disadvantage. For example, the percentage of Black residents is strongly correlated with poverty in Philadelphia and Chicago but not in Los Angeles. In Los Angeles, the percentage of Hispanic residents is strongly correlated with poverty. Within each city, we categorize concentrated disadvantage into five quantiles (0–20%, 20–40%, 40–60%, 60–80%, and 80–100%) for each hexagonal cell.

Following McNulty and Holloway (2000), we include a dichotomous measure of whether or not a hexagon has public housing complex using publicly available data from each city's public housing authority (Chicago Data Portal, 2021a; Housing Authority of Baltimore City, 2021; Los Angeles City Controller, 2021; New York City Housing Authority, 2021; Open Data DC, 2021a; Philadelphia Housing Authority, 2021).

3.4. Analytic strategy

We estimate a set of Poisson regressions with the following specification:

$$log(\lambda)_{ic}^{t} = \alpha + \beta\ \ \mathrm{HHI_{ic}} + \Gamma\ \ \mathrm{Landuse_{ic}} + \overrightarrow{X}\ \mathrm{Controls_{ic}} + \zeta\ \ \mathrm{Spatial.lag_{ic}^{t}} + \epsilon_{ic} \tag{3}$$

where i stands for the hexagon cell in the city grid, c denotes the city, t denotes the time period, α is an intercept, β is a coefficient the HHI Index, and Γ represents the matrix of coefficients that capture land use groups (residential, commercial, industrial, open space, and public facility represented by five quantiles (0%; 1% to 10%; 10% to 25%; 25% to 50%; 50% to 100%), median street betweenness, and whether a grid cell contains streets or buildings. Vector $\overrightarrow{X}$ represents coefficients for the socioeconomic measures of disadvantage, residential stability index, the presence of public housing buildings, and total residential population in each hexagon cell. We also include a spatial lag for the shootings, ζ, which is an average count of shootings in areas adjacent to the cell i for each time period t.

To account for the possible overdispersion in counts of shootings, we estimate standard errors using a robust variance-covariance matrix, which consistently estimates standard errors in case of inequality of the first two moments of the Poisson distribution. This approach is similar to the use of a quasi-Poisson estimator (Berk & MacDonald, 2008). In our main specification, we cluster standard errors at the city district level. This helps us to account for the unmeasured spatial auto-correlation between shootings within each city district unit and reduces bias in the standard errors. To check for robustness, we also re-estimate our model on pooled city data with various clusters (police districts and census tracts), a robust variance-covariance matrix without clustering, and a negative Binomial estimator. The results are robust to various methods that adjust for spatial auto-correlation. We also re-estimate our model with census block groups as units of analysis.

Using the regression model specified in Eq. 3, we proceed with several steps. First, we report the results from the estimated model for the number of shootings per hexagon for the entire period of 2018 to 2021. Second, we re-estimate the same model for shootings in 2018–2019 and 2020–2021 separately. We then compare these estimates using seemingly unrelated regression (SUR) estimation to account for correlated error terms between models. Finally, we check whether the results we report are robust to alternative specifications of Eq. 3.

4. Results

4.1. Descriptive statistics and concentration of shootings

The descriptive patterns show that shootings are geographically concentrated. Fig. 3 shows a Lorenz curve of the cumulative proportion of shootings by proportion of land area in each city (Steenbeek & Weisburd, 2016). In Los Angeles and New York, 5–7% of the land area accounts for all the shootings over the 4-year period, whereas for other cities this percentage is up to 17–19%. Cities with the highest rates of shootings per land area have the least amount of spatial inequality in shootings, driven by the fact that there are fewer areas with no shootings (Chalfin, Kaplan, & Cuellar, 2021). Generally, 50% of shootings happen in the interval of 1–5% of the urban area.

Table 1 shows the descriptive statistics for the variables used in the estimates of shooting rates per area. We interpolate the socioeconomic variables from the census block groups which introduces some measurement error in population estimates. In terms of land use, residential areas consistently occupy more space (31–47%) than land with commercial buildings (4–9%), public facilities (5–10%), open space (11–22%), and industry (2–10%). Baltimore is the most industrial city in terms of land use, while D.C. has more parks, recreation spaces, and public facilities.

To make the data more transparent we also present the means and standard deviations of variables used in the creation of disadvantage and stability indices. Washington D.C. and Los Angeles ($103 K and $99 K) have the highest yearly median household income, and Philadelphia ($57 K), Chicago ($61 K), and Baltimore ($63 K) have the lowest. The District of Columbia has the largest income inequality as shown by its highest variance in median household income. The percentage of female-headed households is approximately the same in all cities, with about a third having no father present in the household.

Los Angeles has the smallest percentage of Black residents and the largest percentage of Hispanic residents than the other five cities. On average, a hexagonal cell with a diameter of 300 m (roughly 1000 ft) has 130 to 490 residents, with the highest mean population density in New York City and the lowest in Baltimore.

In terms of street connectivity, the median street betweenness ranges between 4.8 to 7.6, indicating that within each hexagon the median street is intersected 4 to 8 times.Los Angeles has the smallest median betweenness due to the lowest overall street density.

4.2. Regression results

Table 2 presents the descriptive associations from the Poisson regression estimates. We report results in incidence rate ratios to make the results easier to interpret. The share of residential and commercial buildings exhibits an almost linear association with the count of shootings per area: the increase in the percentage of these buildings is associated with a higher shooting rate. Compared to a reference level of a cell with 25–50% of residential land use and 1–10% of commercial land use, cells with smaller residential density have fewer shootings. These patterns are consistent across the cities. Areas with no residential buildings whatsoever have 31% (Los Angeles) to 69% (Baltimore) fewer shootings compared to areas with the average amount of residential housing. However, the further increase in the residential density to 50–100% does not seem to affect the shooting intensity in a unified way. In New York, Washington D.C., and Baltimore, areas dominated by

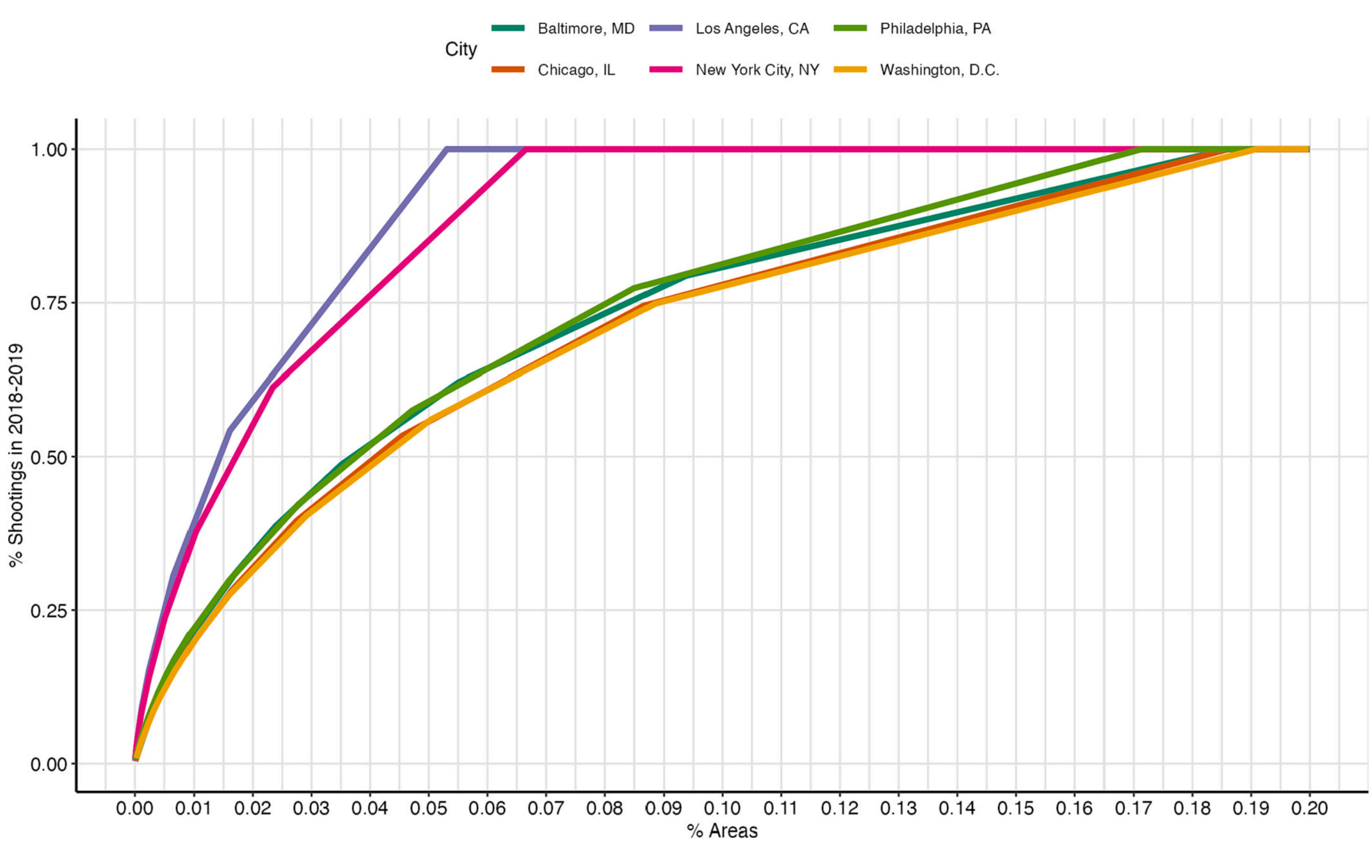

Fig. 3. Concentration of shootings in 2018–2021 across cities.

Table 1
Descriptive statistics of six city-level datasets. Columns show means and (standard deviations)

	City					
	Baltimore	Chicago	LA	NYC	Phila.	D.C.
Total # of shootings, 2018–2019	0.45	0.39	0.08	0.11	0.38	0.41
	(1.35)	(1.14)	(0.42)	(0.54)	(1.18)	(1.17)
Total # of shootings, 2020–2021	0.45	0.60	0.12	0.23	0.60	0.54
	(1.43)	(1.64)	(0.53)	(0.90)	(1.76)	(1.50)
Landuse: % residential	47.05	32.42	45.00	32.20	31.29	40.51
	(40.73)	(26.21)	(34.56)	(26.70)	(27.27)	(40.57)
Landuse: % commercial	7.37	5.64	4.85	6.41	5.61	9.90
	(18.55)	(11.65)	(13.34)	(11.95)	(13.03)	(22.51)
Landuse: % public facilities	9.96	5.70	5.65	5.96	6.05	11.73
	(21.91)	(14.01)	(15.52)	(15.36)	(14.61)	(26.08)
Landuse: % open space	13.90	11.31	14.89	16.92	17.36	22.02
	(28.23)	(23.99)	(31.49)	(28.30)	(27.52)	(33.44)
Landuse: % industrial	10.47	6.04	6.84	2.47	7.34	2.05
	(25.66)	(17.20)	(20.91)	(9.57)	(18.55)	(10.82)
Landuse diversity (HHI)	0.00	0.00	0.00	0.00	0.00	0.00
	(0.20)	(0.20)	(0.18)	(0.19)	(0.20)	(0.19)
Disadvantage index	0.00	0.00	0.00	−0.00	−0.00	0.00
	(1.54)	(1.75)	(1.53)	(1.57)	(1.65)	(1.81)
Median household income, *1000$	63.84	61.17	99.83	79.43	57.55	103.25
	(37.46)	(33.38)	(56.79)	(33.81)	(27.69)	(60.35)
% Black	57.03	37.88	7.71	22.28	35.24	45.64
	(35.16)	(39.64)	(12.85)	(28.36)	(32.81)	(35.77)
% Hispanic	6.14	26.76	35.15	22.61	12.03	9.09
	(12.58)	(28.47)	(28.76)	(19.92)	(15.63)	(8.34)
% poor	21.18	19.39	11.29	14.13	19.28	14.19
	(21.25)	(14.75)	(10.44)	(12.88)	(15.47)	(13.60)
% unemployed	8.86	10.25	5.49	6.25	9.09	8.16
	(9.41)	(9.31)	(4.14)	(6.80)	(8.23)	(7.75)
% single mothers	36.77	36.26	34.09	34.70	35.02	30.28
	(15.71)	(12.56)	(12.69)	(13.24)	(13.87)	(14.49)
Stability index	−0.00	0.00	0.00	−0.00	0.00	−0.00
	(1.11)	(1.18)	(1.16)	(1.17)	(1.22)	(1.16)
% owner occupied households	52.13	51.49	56.37	47.97	56.87	43.82
	(26.25)	(24.17)	(29.57)	(29.74)	(22.37)	(30.26)
% recently moved	9.74	9.16	7.60	7.55	9.66	11.11
	(8.08)	(6.92)	(6.37)	(8.29)	(7.56)	(8.04)
Public housing in cell (dummy)	0.01	0.03	0.02	0.06	0.01	0.10
	(0.09)	(0.16)	(0.15)	(0.24)	(0.08)	(0.30)
Residential population in a single cell, thousands	0.13	0.19	0.19	0.49	0.21	0.18
	(0.12)	(0.18)	(0.24)	(0.55)	(0.20)	(0.19)
Median street betweenness	6.32	5.47	4.82	7.54	7.62	5.80
	(5.22)	(3.83)	(4.28)	(5.30)	(6.65)	(5.39)
No streets or land use (dummy)	0.14	0.17	0.21	0.13	0.15	0.20
	(0.35)	(0.37)	(0.41)	(0.34)	(0.35)	(0.40)
Number of observations (hexagons)	4520	14,117	24,176	17,276	7437	3929

residential land use have even more shootings, while in Los Angeles and Philadelphia, these areas are associated with lower shooting counts per area.

In terms of other land uses, commercial land use is consistently associated with higher counts of shootings. Compared to the base level of 1–10% of commercial buildings in the cell, having no such buildings is associated with a lower rate of shootings by 18–33%. Having more commercial establishments in an area seems to be positively correlated with higher shooting counts. While not all the coefficients are significant, the direction and magnitude of associations suggest that areas with a higher share of commercial land use generally have higher yearly counts of shootings. Areas with no public facilities have significantly lower (10–39%) incidence of shootings compared to areas with some public facilities. The share of parks and open spaces and their association with shootings are similar to that of public facilities. Areas with the dominant share of open space in two cities (Philadelphia and Washington D.C.) exhibit a rate of shootings statistically lower compared to the reference group. The variation in industrial land use is not consistently associated with differences in shootings per area across cities. However, in Chicago, New York, and Philadelphia the areas with predominantly industrial buildings occupying at least 50% of land use have 50–69% fewer shootings.

Less land use diversity (HHI) is associated with higher counts of shootings in Baltimore, Chicago, and Philadelphia. Other cities exhibit a similar direction of association that is not statistically significant. The incident rate ratios of 224–644% reported in the table show the increase in the shooting rate if the area has no relative land use diversity compared to an area with maximum land use diversity. In other words, we see suggestive evidence of the negative association between land use diversity and shootings, which is likely to be correlated with the fact that many shootings occur in predominantly residential areas. The areas with more mixed land use on average have fewer shootings.

Public housing location is associated with higher counts of shootings in New York City, Philadelphia, and Washington, D.C. Having public housing nearby is associated with a 68–69% higher count of shootings per area in New York and Philadelphia, and 42% higher count in shootings in Washington D.C. The differences between these cities may reflect higher spatial concentrations of poverty within public housing relative to other neighborhoods.

Across all cities, concentrated disadvantage remains a significant association with higher counts of shootings per area. In Los Angeles and New York City, there are 4 times as many shootings in areas belonging to the upper quantile (top 20%) of concentrated disadvantage relative to the median quantile, compared to a difference of 1.6 times in Baltimore.

Table 2
Regression estimates of shootings in six cities. Exponentiated coefficients (incident rate ratio) are reported. The standard errors are clustered at the police district level

	1	2	3	4	5	6
	Baltimore	Chicago	LA	NYC	Phila.	DC
Residential landuse						
0%	0.31**	0.37***	0.69*	0.42***	0.32***	0.28*
	(0.11)	(0.07)	(0.12)	(0.06)	(0.06)	(0.16)
1–10%	0.33***	0.67***	0.91	0.70**	0.61***	0.44***
	(0.07)	(0.06)	(0.14)	(0.08)	(0.05)	(0.09)
10–25%	0.66*	0.76***	0.87	0.83*	0.92	0.86
	(0.11)	(0.04)	(0.08)	(0.06)	(0.07)	(0.19)
25–50%	1	1	1	1	1	1
	(.)	(.)	(.)	(.)	(.)	(.)
50–100%	1.46***	0.95	0.75***	1.06	0.9	1.11
	(0.14)	(0.05)	(0.05)	(0.08)	(0.05)	(0.18)
Commercial landuse						
0%	0.72**	0.77***	0.76***	0.67***	0.72***	0.82*
	(0.09)	(0.03)	(0.05)	(0.05)	(0.05)	(0.08)
1–10%	1	1	1	1	1	1
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	1.53	1.56***	1.50***	1.16*	1.32***	1.09
	(0.34)	(0.1)	(0.16)	(0.07)	(0.09)	(0.16)
25–50%	2.72***	1.87***	1.50*	1.39**	1.72***	1.49**
	(0.53)	(0.14)	(0.24)	(0.14)	(0.17)	(0.19)
50–100%	4.00***	2.12***	1.2	1.91**	1.17	1.69
	(0.81)	(0.37)	(0.18)	(0.41)	(0.25)	(0.47)
Public facilities landuse						
0%	0.61***	0.90*	0.88**	0.86*	0.79***	0.96
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)
1–10%	1	1	1	1	1	1
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	1.02	1.03	0.86	0.92	0.89*	0.87
	(0.12)	(0.06)	(0.08)	(0.07)	(0.04)	(0.07)
25–50%	1.03	1.06	0.76*	0.98	0.72***	1.07
	(0.31)	(0.1)	(0.1)	(0.14)	(0.07)	(0.16)
50–100%	1.44	1.12	0.34***	0.75	1.17	0.46***
	(0.29)	(0.2)	(0.08)	(0.23)	(0.3)	(0.08)
Open space landuse						
0%	0.64**	0.73***	0.88	0.87*	0.65***	0.95
	(0.09)	(0.04)	(0.1)	(0.06)	(0.05)	(0.09)
1–10%	1	1	1	1	1	1
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	1.11	1.18*	1.17	1.05	1.14	0.84
	(0.17)	(0.09)	(0.24)	(0.1)	(0.09)	(0.14)
25–50%	0.72	1.1	1.08	0.8	1.02	0.76
	(0.16)	(0.09)	(0.26)	(0.1)	(0.12)	(0.14)
50–100%	1.04	0.98	1.09	0.57*	0.37***	0.45***
	(0.31)	(0.12)	(0.4)	(0.14)	(0.07)	(0.07)
Industrial landuse						
0%	1.01	0.87	0.79	1	1.02	0.79
	(0.05)	(0.07)	(0.1)	(0.06)	(0.05)	(0.15)
1–10%	1	1	1	1	1	1
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	1.24	1.01	1.18	0.96	0.93	1.01
	(0.14)	(0.09)	(0.19)	(0.14)	(0.11)	(0.31)
25–50%	2.17***	0.96	1.01	1.24	0.68**	0.72
	(0.49)	(0.09)	(−0.14)	(0.27)	(0.09)	(0.17)
50–100%	1.01	0.50***	0.89	0.31**	0.32***	0.72
	(0.41)	(0.08)	(0.13)	(0.13)	(0.09)	(0.25)
Landuse diversity (HHI)	6.44***	2.24***	1.7	1.17	3.02***	1.37
	(3.59)	(0.5)	(0.51)	(0.35)	(0.88)	(0.59)
Disadvantage index quantiles						
0–20%	0.17***	0.29***	0.28***	0.46***	0.28***	0.24***
	(0.06)	(0.06)	(0.1)	(0.11)	0.05	0.05
20–40%	0.59***	0.59***	0.55***	0.46***	0.34***	0.45***
	(0.08)	(0.07)	(0.08)	(0.08)	(0.05)	(0.06)
40–60%	1	1	1	1	1	1
	(.)	(.)	(.)	(.)	(.)	(.)
60–80%	1.31*	1.98***	2.11***	3.00***	2.44***	1.73*

(*continued on next page*)

Table 2 (*continued*)

	1	2	3	4	5	6
	Baltimore	Chicago	LA	NYC	Phila.	DC
	(0.16)	(0.21)	(0.35)	(0.32)	(0.36)	(0.39)
80–100%	1.59***	2.48***	4.50***	4.80***	3.21***	2.68***
	(0.2)	(0.27)	(1.02)	(0.62)	(0.43)	(0.59)
Stability index	0.94	0.90***	0.92	0.81***	1.04	0.81***
	(0.06)	(0.02)	(0.05)	(0.04)	(0.03)	(0.04)
Public housing in cell (dummy)	1.2	1.15*	1.11	1.69***	1.68***	1.42***
	(0.34)	(0.08)	(0.08)	(0.09)	(0.16)	(0.07)
Residential population in cell, thousands	3.12**	1.78*	1.40**	1.29***	1.73***	2.08**
	(1.27)	(0.42)	(0.15)	(0.05)	(0.25)	(0.49)
Median street betweenness	1.06***	1.05***	1.06***	1.01**	1.03***	1
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
No streets or land use (dummy)	0.01***	0.08***	0.18***	0.01***	0.05***	0.19***
	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.06)
Spatial lag	1.17***	1.16***	1.58***	1.29***	1.10***	1.16***
	(0.02)	(0.02)	(0.08)	(0.04)	(0.01)	(0.05)
Observations	4,520	14,117	24,176	17,276	7,437	3,929

Note: Standard errors in parentheses, *$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$ (2-tailed tests).

These estimates are consistent with the descriptive data shown in Lorenz curves in Fig. 3 and indicate that the cities with the lowest shooting rates have the greatest spatial inequality in shootings.

The median street betweenness and the residential density are positively associated with shootings, while having no streets or designated land use parcels in a hexagon cell is associated with significantly fewer shootings per area.

We estimated marginal effects from our model to visually illustrate how the association between residential land use and shootings varies by level of concentrated disadvantage. Fig. 4 shows the change in the expected yearly shooting count in an area relative to the share of residential land use and disadvantage index in each city.

First, the figure shows that the shape of the association between residential land use and shootings varies and is not always linear. The green line for Baltimore and Washington D.C. is monotonically increasing, suggesting the share of residential buildings in the area is linearly predictive of the shooting rates. The slope for Philadelphia and Chicago grows until the residential share is larger than 25–50%, peaks, and then slightly decreases. By contrast, the slope for Los Angeles and New York City is almost flat.

Second, concentrated disadvantage multiplies the association between residential land use and shootings. However, the exact relationship varies across cities. In Baltimore, the difference between medium and top 20% of disadvantaged neighborhoods with the same share of residential buildings is smaller than between bottom and medium 20%. In other words, the shooting risk in an average neighborhood in Baltimore is closer to the one in the most disadvantaged neighborhoods rather than it is to neighborhoods with the lowest levels of concentrated disadvantage. Other cities exhibit the opposite pattern and show the predicted shootings disproportionately increase among the top 20% of

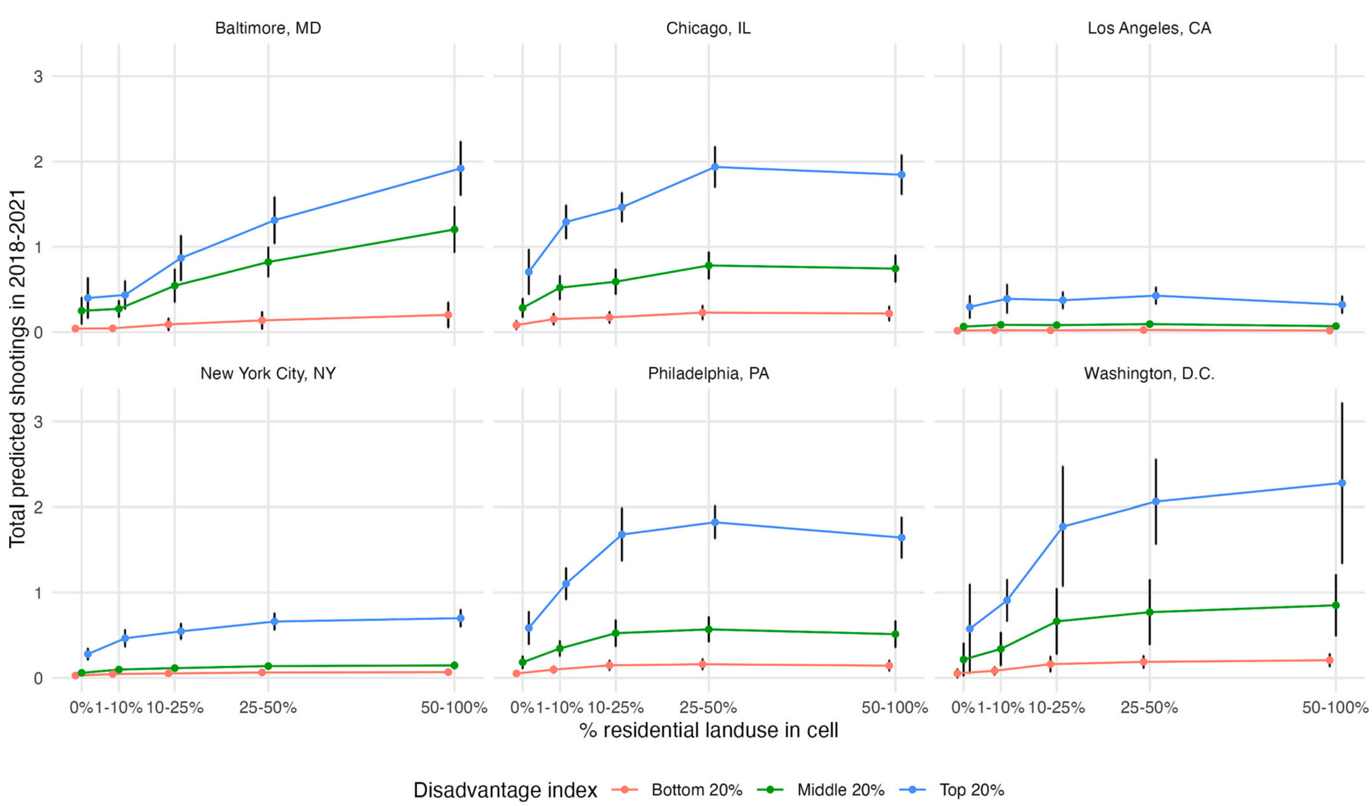

Fig. 4. Marginal effects of residential density on shootings.

the most disadvantaged neighborhoods. The model predicts in the top 20% approximately 2 shootings in Chicago, Philadelphia, and Washington D.C. over a 4-year period, which is a large magnitude in an area with a radius of 1000 ft.

4.3. Shootings before and during pandemic

To look at whether there are spatial changes in the shootings in 2020–2021 compared to 2018–2019, we estimate regressions using seemingly unrelated regression (SUR) for each time period separately (Light & Harris, 2012). We use SUR to account for the correlation in covariance matrices across time periods. In other words, we want to account for the fact that we have two separate models which differ in the dependent variable and its spatial lag but ultimately have the same independent variables and resulting covariance matrices. This allows us to conduct joint hypothesis tests of parameters between two models, or whether the role of independent variables in predicting shootings has changed between the 2020–2021 and 2018–2019 models.

Table 3 shows the results and indicates that there are no statistically significant differences in the coefficients between 2018-2019 and 2020–2021. Only Philadelphia shows there was a significant change in shootings in 2020–2021 in areas with none or almost no residential buildings (an increase of 23–25% relative to the reference level), and 81% less in areas with a 25-50% share of commercial land use. Importantly, we do not observe a disproportionate increase of shootings in the most disadvantaged areas compared to the middle quantile. These findings indicate that the increase in shootings was not attributable to specific land use and area characteristics, and are suggestive of a general spread of shootings across spaces.

Using the estimated models for the 2018–2019 and 2020–2021 periods, we also separately estimate the marginal effects of concentrated disadvantage quantiles on shootings. Fig. 5 shows rates of shootings in 2018–2019 compared to 2020–2021 by concentrated disadvantage across cities. In Chicago, New York, and Philadelphia, shootings in disadvantaged areas have significantly increased in 2020–2021 relative to 2018–2019. One can clearly see that in absolute rates the greatest burden for the increase in shootings was borne by the most economically disadvantaged areas of Chicago, New York, and Philadelphia. These findings are consistent with other descriptive work showing that shootings increased in absolute rates the most in areas of concentrated disadvantage in these cities during the pandemic (MacDonald et al., 2022). The magnitude of change in Washington D.C. and Los Angeles is smaller but also increasing in direction. Baltimore does not exhibit a change in shootings at any level of concentrated disadvantage, which is

Table 3
Change in coefficients predicting shootings between 2018 -2019 and 2020–2021. The models are estimated using SUR. The significance is calculated using a two-sided paired *t*-test with pooled variance. The reference categories for binned variables are not shown.

Baltimore		Chicago	LA	NYC	Phila.	D.C.
Residential land use						
0%	0.07	0.04	0.13	0.17	0.23**	−0.01
1–10%	0.00	0.07	0.23	0.21	0.25***	0.14
10–25%	−0.11	−0.03	0.25*	−0.02	0.10	0.1
>50%	−0.53	−0.07	−0.05	0.12	−0.07	0.11
Commercial land use						
0%	−0.06	−0.06	−0.13	0.13	0.06	0.17
10–25%	−0.35	−0.02	−0.10	−0.12	−0.19	0.25
25–50%	−0.17	0.12	−0.15	−0.05	−0.81***	0.26
>50%	−0.65	0.11	−0.20	−0.74	−0.84	0.32
Public facilities land use						
0%	0.06	0.09	0.00	0.01	0.07	−0.02
10–25%	0.12	−0.05	0.07	−0.20	0.07	−0.03
25–50%	−0.15	0.19	−0.11	−0.34	−0.20	−0.5*
>50%	−0.12	0.03	−0.06	−0.68	−0.53	−0.17
Open space land use						
0%	−0.10	−0.01	0.11	0.00	0.07	−0.12
10–25%	0.35	0.11	0.09	0.05	0.03	−0.25
25–50%	−0.46	0.04	0.20	0.16	−0.15	0.07
>50%	0.13	0.03	0.12	−0.13	0.00	−0.15
Industrial land use						
0%	0.06	0.02	0.10	−0.10	−0.07	−0.3
10–25%	−0.3	0.11	0.08	−0.17	−0.12	−0.53
25–50%	1.22	0.3*	0.26	−0.48	−0.32*	0.03
>50%	−0.19	0.04	0.35	−0.46	−0.25	−0.1
Landuse diversity (HHI)	0.63	−0.16	0.65	−0.57	−1.35	−0.52
Disadvantage index quantiles						
0–20%	0.06	0.13	0.27**	0.20	−0.01	−0.08
20–40%	−0.01	0.03	0.13	0.00	−0.13	0.03
60–80%	−0.02	0.33	0.11	0.05	−0.20	−0.23
80–100%	−0.09	0.24	−0.19	0.3	−0.36	−0.69
Stability index	0.00	−0.01	−0.05	−0.12	−0.04	−0.06
Public housing in cell (dummy)	0.39	−0.01	−0.12	−0.10	0.37	0.07
Residential population	0.00	0.00	0.00	0.00	0.00	0.00
Median street betweenness	0.00	0.01	−0.01	0.01	−0.01	−0.01
No streets or land use (dummy)	−0.03***	0.03	−0.11*	0.01***	0.01	0.00
Intercept	0.08	0.06	0.01	0.03	0.14**	0.32

Note: Standard errors in parentheses, *$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$ (2-tailed tests).

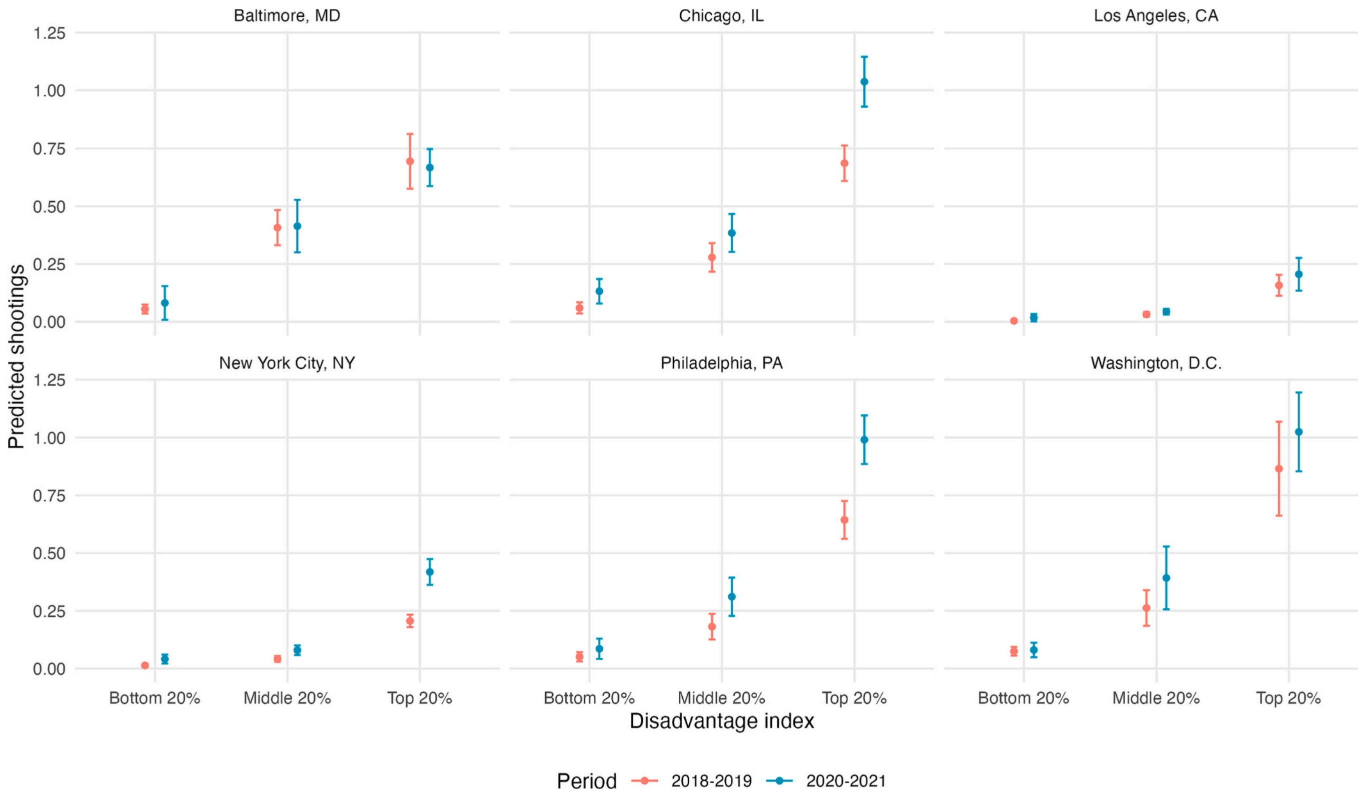

Fig. 5. Changes in shooting intensity between 2018 and 2019 and 2020–2021 across concentrated disadvantage quantiles.

consistent with the trends showing that the city did not experience an epidemic rise in shootings during the pandemic.

5. Robustness checks

To assess the robustness of our results we estimated a range of alternative model specifications. First, in the interest of parsimony, we pool our city-level analytic databases into one cross-section and add city intercepts to adjust for between-city differences in shooting rates. We then estimate a Negative Binomial regression model, along with several different approaches to ensure that the results are not driven by different forms of spatial auto-correlation. We also estimate models using census block groups instead of hexagonal units. Table 4 reports the results. The coefficients and standard errors across all specifications are remarkably similar, with the exception of the census block groups model. We interpret this as evidence that our findings are not driven by how spatial correlation impacts standard errors.

However, the comparison between columns (5) and (6) in Table 4 shows that results for the model with census block groups differ, such that the magnitudes and statistical significance of the land use coefficients are much weaker. Residential land use in this specification does not seem to be predictive of variation in shooting rates, while the concentration of commercial establishments still shows a positive association at a smaller magnitude with shootings. Other variables, such as concentrated disadvantage and public housing, have similar magnitudes and significance. The difference in land use effects might be explained by the different levels of aggregation. In the hexagonal grid spatial analysis, the percentages of land use types are the same in absolute terms across different cells, because all the cells have the same area and shape. Census block groups differ in areas and shapes, and a large block group with 25% of residential land use might have more residential buildings in terms of area than a smaller block group with 80% of residential land use. In other words, modeling land use using percentages at the level of census block groups might result in biased estimates due to varying sizes of census blocks and associated unobserved differences, which also might explain why land use estimates are different than with a hexagonal grid.

6. Discussion

This paper examined the spatial context of shootings across six cities and whether the environmental and socioeconomic correlates of shootings changed during the 2020–2021 pandemic period. We focused on the association between shootings and various types of land use, which we measured using five broad categories to capture the spatial intensity and diversity in land uses across places. We examine these associations while controlling for a range of social and environmental features of places, while simultaneously accounting for spatial correlation. Overall the results suggest that shootings per area are higher in areas with a higher concentration of residential and commercial land uses, even after controlling for a number of social and environmental characteristics. These results are consistent with research on the spatial association between land use and violent crime in an earlier time period in Indianapolis, IN (Stucky & Ottensmann, 2009). By pooling data from several major cities and a flexible model, we show that single-use density (commercial or residential) and less diversity of land use in general relative to other nearby areas are generally associated with more shootings in an area. These findings are largely consistent with place-based theories of crime that emphasize the importance of a diversity of uses of land uses for generating more foot traffic, "eyes upon the street" (Jacobs, 1961), and informal social controls (Sampson, 2021) that help mitigate an area from becoming a hot spot for violence (Jean, 2007).

By examining multiple cities this study shows the heterogeneity in the estimates of the association between shootings and various place-based correlates. For example, public housing is strongly associated with shootings only in New York City, Philadelphia, and Washington D. C., despite being an important factor explaining crime concentration for

Table 4
Regression estimates for alternative specifications. Exponentiated coefficients (incident rate ratio) are reported. Columns with models (2) and (6) report robust standard errors. Column labels show the estimators employed. City intercepts are included but not shown.

	(1)	(2)	(3)	(4)	(5)	(6)
	NB	Poisson	Poisson	Poisson	Poisson	Poisson
Residential landuse						
0%	0.49***	0.39***	0.39***	0.39***	0.39***	1.10
	(0.02)	(0.03)	(0.05)	(0.04)	(0.03)	(0.16)
1–10%	0.70***	0.64***	0.64***	0.64***	0.64***	1.20**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.08)
10–25%	0.81***	0.80***	0.80***	0.80***	0.80***	1.09
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
25–50%	1.00	1.00	1.00	1.00	1.00	1.00
	(.)	(.)	(.)	(.)	(.)	(.)
50–100%	0.99	0.95	0.95	0.95	0.95	0.89**
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Commercial landuse						
0%	0.69***	0.71***	0.71***	0.71***	0.71***	0.80***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
1–10%	1.00	1.00	1.00	1.00	1.00	1.00
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	1.40***	1.38***	1.38***	1.38***	1.38***	1.06
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)
25–50%	1.73***	1.70***	1.70***	1.70***	1.70***	1.12
	(0.07)	(0.08)	(0.10)	(0.10)	(0.08)	(0.07)
50–100%	1.77***	1.63***	1.63***	1.63***	1.63***	1.07
	(0.11)	(0.12)	(0.15)	(0.14)	(0.14)	(0.13)
Public facilities landuse						
0%	0.83***	0.82***	0.82***	0.82***	0.82***	0.92**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
1–10%	1.00	1.00	1.00	1.00	1.00	1.00
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	0.98	0.97	0.97	0.97	0.97	0.98
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
25–50%	1.06	0.95	0.95	0.95	0.95	0.90
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
50–100%	0.88	0.71***	0.71**	0.71*	0.71**	0.85
	(0.06)	(0.07)	(0.08)	(0.10)	(0.08)	(0.13)
Open space landuse						
0%	0.83***	0.80***	0.80***	0.80***	0.80***	0.84***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)
1–10%	1.00	1.00	1.00	1.00	1.00	1.00
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	1.06	1.12***	1.12*	1.12**	1.12**	1.01
	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)	(0.04)
25–50%	1.03	0.98	0.98	0.98	0.98	0.90
	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
50–100%	0.84**	0.65***	0.65***	0.65***	0.65***	0.92
	(0.05)	(0.05)	(0.08)	(0.07)	(0.06)	(0.09)
Industrial landuse						
0%	0.91**	0.91**	0.91*	0.91*	0.91**	0.99
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)
1–10%	1.00	1.00	1.00	1.00	1.00	1.00
	(.)	(.)	(.)	(.)	(.)	(.)
10–25%	1.09	1.02	1.02	1.02	1.02	0.99
	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)
25–50%	1.18**	0.98	0.98	0.98	0.98	0.95
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
50–100%	0.91	0.69***	0.69	0.69	0.69**	1.11
	(0.07)	(0.06)	(0.13)	(0.13)	(0.08)	(0.16)
Landuse diversity (HHI)	1.88***	2.34***	2.34***	2.34***	2.34***	0.94
	(0.16)	(0.23)	(0.31)	(0.33)	(0.25)	(0.12)
Disadvantage index quantile						
0–20%	0.33***	0.28***	0.28***	0.28***	0.28***	0.30***
	(0.01)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)
20–40%	0.56***	0.52***	0.52***	0.52***	0.52***	0.60***
	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
40–60%	1.00	1.00	1.00	1.00	1.00	1.00
	(.)	(.)	(.)	(.)	(.)	(.)

(*continued on next page*)

Table 4 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)
	NB	Poisson	Poisson	Poisson	Poisson	Poisson
60–80%	1.92***	2.09***	2.09***	2.09***	2.09***	1.77***
	(0.05)	(0.07)	(0.14)	(0.12)	(0.08)	(0.06)
80–100%	2.91***	3.16***	3.16***	3.16***	3.16***	2.30***
	(0.08)	(0.10)	(0.24)	(0.19)	(0.13)	(0.08)
Stability index	0.90***	0.92***	0.92***	0.92***	0.92***	0.98
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Public housing in cell (dummy)	1.68***	1.55***	1.55***	1.55***	1.55***	1.26***
	(0.06)	(0.05)	(0.08)	(0.07)	(0.05)	(0.04)
Residential population, thousands	1.75***	1.61***	1.61***	1.61***	1.61***	1.21***
	(0.05)	(0.04)	(0.08)	(0.07)	(0.05)	(0.02)
Median street betweenness	1.06***	1.03***	1.03***	1.03***	1.03***	1.00***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
No streets or land use (dummy)	0.11***	0.09***	0.09***	0.09***	0.09***	0.07***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Spatial lag (2018–2021)	1.34***	1.14***	1.14***	1.14***	1.14***	1.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Units	Hexagons	Hexagons	Hexagons	Hexagons	Hexagons	Block groups
Clustered SE?	No	No	Yes, police district	Yes, city council	Yes, census tracts	No
Observations	71,455	71,455	71,455	71,455	71,455	13,648

Note: Standard errors in parentheses, $^{*}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$ (2-tailed tests).

decades (McNulty & Holloway, 2000).

By analyzing these patterns before and during the 2020–2021 rise in shootings, we find that only concentrated disadvantage seems to vary in its association. While concentrated disadvantage did not seem to have a strong association in relative (percentage) terms, shootings increased in absolute rates more in the most disadvantaged areas. This finding is consistent with other research showing that the increase in shootings in several cities we study is associated with spatially concentrated endemic gun violence hot spots, which are also places of durable economic disadvantage (MacDonald et al., 2022).

This study also has broader implications for the understanding of the spatial patterns of gun violence and policy responses. First, the current gun violence intervention programs should not worry as much about spillover or displacement effects in gun violence and focus more on what is driving the concentration of gun violence and making it so durable in the same places. Focusing on efforts to address the environmental risk factors of gun violence hot spots appears to be the most important policy response both before and during the epidemic rise in gun violence in these cities. A variety of place-based approaches have been tried successfully in the past, including focused deterrence, problem-oriented policing, and attending to the environmental neglect in gun violence hot spots (Braga, Piehl, & Hureau, 2009; MacDonald, Branas, & Stokes, 2019; Weisburd et al., 2012). Second, the study also highlights the intra-city inequality in shootings. In cities with a higher intensity of shootings overall, shootings seem to be less concentrated, whereas in safer cities like LA and NYC shootings are hyper-concentrated within the most disadvantaged neighborhoods. This means that, in a city like Baltimore, policymakers should probably focus on broader-scale structural changes to the city than on more focused place-specific strategies to curb the gun violence problem.

Several limitations of our analysis should be noted. First, our analysis is descriptive and the results should not be interpreted as causal effects of land use on gun violence. While the patterns of land use, especially residential segregation with high levels of concentrated disadvantage, have been shown to be enduring and stable for decades (Jacoby et al., 2018), our analysis focuses on the patterns between recent past and current patterns of land use and shootings, not the effects of the change in land use. Recent studies employ rigorous quasi-experimental designs to show how the changes in zoning regulation in places affect crime (Anderson, MacDonald, Bluthenthal, & Ashwood, 2013; Mitre-Becceril & MacDonald, 2021). Future studies should examine the effect of changes in land use on changes in shootings in places.

Second, to ensure comparability between the cities in our analysis, we group various zoning types into several broad categories, which might hide heterogeneity within these categories. For example, there is an important distinction between the concentration and diversity of land uses zoned and the actual uses of this land (e.g., multifamily apartments, bars, restaurants, auto shops). We focus on the broadly conceived land use zones and do not measure the actual land use types in a given area, such as whether a commercially zoned parcel is a bar, restaurant, or another type of place that may attract shootings. Future studies should examine specific land use types at micro-geographies and their association with enduring and epidemic rises in gun violence.

Third, we explicitly focus on the change between 2018 and 2019 and 2020–2021 in shooting rates. Our focus represents only four years of shooting data. Future research should extend this area of inquiry and establish whether patterns of associations between land use and gun violence persist in cities in an era with higher rates of gun violence.

Lastly, we only focus on six large US cities. While the major driving force behind the choice of these cities was the data availability among the 100 most populated cities in the country, we assumed that this list is diverse enough for a meaningful comparison. However, it would be important to understand whether the observations from these cities are also true of other cities around the country as shooting data becomes more available for public use in research.

Appendix A. Appendix

Table A.1
Principal component analysis details for indices

	NYC	Philadelphia	Baltimore	Chicago	DC	LA
Disadvantage index						
% explained variance	0.41	0.45	0.4	0.51	0.55	0.39
Factor loadings:						

(*continued on next page*)

Table A.1 (*continued*)

	NYC	Philadelphia	Baltimore	Chicago	DC	LA
% Black	0.35	0.39	0.5	0.49	0.5	0.19
% Hispanic	0.39	0.26	0.1	−0.17	−0.2	0.53
% poor	0.52	0.51	0.5	0.47	0.48	0.52
% unemployed	0.41	0.39	0.47	0.46	0.45	0.17
Median household income	−0.46	−0.5	−0.52	−0.42	−0.41	−0.56
% single mothers	0.27	0.33	−0.04	0.35	0.32	0.25
Stability index						
% explained variance	0.68	0.75	0.62	0.7	0.67	0.67
Factor loadings:						
% owner occupied households	0.71	0.71	0.71	0.71	0.71	0.71
% recently moved	−0.71	−0.71	−0.71	−0.71	−0.71	−0.71

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