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ORIGINAL PAPER

Accounting for Socio-Economic Context in Quantifying the Attractive and Repellent Influence of Built Environment on Firearms Violence in Multiple Cities

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Abstract

Objectives The objective of this paper is to improve understanding of the spatial relationship of the built environment (BE) with urban gun crime and how the influence of environmental features varies across geographic location and socioeconomic context. Specifically, we analyze associations between incidents of reported firearms violence and distance to built environment features, accounting for neighborhood socio-economic status.

Methods This study compares reported crime data with the outputs from a Monte Carlo Simulation using the *Network Cross-K Function for Stochastic Spatial Events* on street networks. Where data is available, we examine ten features—transit stations, universities/colleges, convenience stores, gas stations, liquor licenses, alcohol outlets, tobacco retailers, lodging, restaurants, and schools—across diverse metropolitan areas to uncover features that exert "attractive" or "repellent" influence on firearms violence. We present results from four U.S. cities and examine how results vary by socio-economic status of census tracts.

Results Attractive features include tobacco retailers in Pittsburgh, hotels/motels, alcohol outlets, and restaurants in New Orleans, and rail transit stations in Los Angeles. We uncover localized attractive and repellent relationships within the lowest and highest socioeconomic areas. We also identify several firearms crime repellents, including universities/colleges and public/private schools.

Conclusions We find that attractors vary by city and socio-economic status, indicating that the unique underlying environmental context of each city facilitates firearms crime differently.

Keywords Firearms violence · Built environment · Geospatial analysis · Hot spot · Network location

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The United States faces an unprecedented challenge with regards to firearms violence. While crime rates have been generally decreasing, firearm-related injuries and homicides are on the rise. In 2017, firearms facilitated a staggering 14,542 homicides (Kochanek et al. 2019), and gun assault rates in cities increased by another eight percent between 2019 and 2020 (Rosenfeld et al. 2021). While research shows that firearm violence is not uniformly distributed throughout the environmental landscape, the geospatial associations between built environment features and gun crime are not well understood. This study applies geospatial analysis to four U.S. cities—Detroit, Los Angeles, New Orleans, and Pittsburgh—with the objective of quantifying the influence of certain built environment features on the locations of firearms violence and exploring the role of socioeconomic context.

The fact that crime is geographically clustered in specific areas has been well documented by a large body of research (Braga et al. 2014; Caplan et al. 2011; Eck et al. 2005, 2007; Kennedy et al. 2011; Weisburd et al. 2009, 2017). Research demonstrates that fatal shootings, in particular, tend to be heavily clustered in specific areas (Aufrichtig et al. 2017). More recent research, however, demonstrates that some methods for measuring crime concentration can overstate the extent of clustering (Chalfin et al. 2021). Building off of this research and a method employed in Xu and Griffiths (2016), we analyze the proximal concentration of firearm crimes to built environment features by comparing observed distributions to counterfactual distributions of randomly assigned firearm crimes on street networks.

Whether socio-economic conditions help explain the proximal relationships identified between built environment features and firearm crime is an open question. Research suggests that built environmental factors, such as foreclosures, are highly correlated with features of the social environment, such as concentrated poverty, and these features are attractors of crime. In a study of New York City, Ellen et al. (2013) examine the effects of removing foreclosures on violent and public order crime. For a given street block, they find marginal increases in foreclosures is associated with more total, violent, and public order crimes. The result is more pronounced in medium- to high-crime neighborhoods, suggesting differential relationships to built environment features across neighborhoods. Using data from Chicago in the late 1990s, Bernasco and Block (2009) examine how racial and ethnic segregation affects the spatial target choices of robbers, controlling for neighborhood population, employment, collective efficacy, distance, and drug and prostitution arrests at the census tract level. Authors find robberies are more common in areas with retail businesses, yet the degree of this relationship differs across neighborhoods. These results are important because they imply that socio-economic context plays a role in explaining distal relationships between built environment features and firearm crimes. This study addresses neighborhood-level exposure and vulnerability to crime by identifying feature types and locations that influence firearms violence because "targeting the risk and protective factors of violence at the community level will likely engender the greatest change" (American Psychological Association 2021).

The objective of this paper is to improve understanding of the spatial relationship between built environment (BE) and urban crimes involving firearms, with focus on the varied influence of environmental features across geographic location and socioeconomic context. To achieve this aim, we apply the Network Cross-K function for stochastic spatial events to analyze associations between the locations of reported firearms crimes and built environment features, accounting for neighborhood socio-economic status. This study builds on work by Xu and Griffiths (2016) for Newark, NJ where we leverage a similar approach and expand the methodology to account for socio-economic context. Our data includes transit stations and colleges/universities in all four cities, so we present those

results first, before examining schools, liquor stores, convenience stores, tobacco retailers, fast-food restaurants, and gas stations where data is available.

This paper makes three contributions to the literature. First, while gun crime attractors have been explored in the Northeast United States, these analyses have not been appropriately extended to other regions. This study examines four cities that vary in geographic region, total area, population density, and demographic characterization, thus providing an excellent opportunity to examine trends across cities. Second, we improve a metric of risk called Firearms Incident Density, which enables us to assess how risk dissipates with increasing distance from a feature and make comparisons across features. Third, and perhaps most importantly, we introduce a method for examining the influence of socio-economic status on the proximity of built environment features to firearms violence. Our insights can help better understand the role of the built environment and socio-economic context in reported firearm crime, facilitating policies and interventions to improve urban security.

This paper focuses on firearm crime, in part, because we may uncover insights that explain why other types of crimes occur in proximity to certain types of built environment features. On the one hand, there are theoretical reasons to expect common risk factors for firearm-specific crime and assaults or robberies more generally; in 2018, approximately 39% of robberies and 26% of aggravated assaults involved firearms. On the other hand, firearm violence may present some unique factors that have not yet received substantial attention in the literature. Specifically, the determinants of firearm crime are a function of opportunity, but they are also inherently linked to the decision to carry or use a firearm. For example, facilities may be crime generators for assaults due to the confluence of large groups of people, but may be protective for firearm-related assaults if the facility bans the carrying of firearms (e.g., schools, stadiums, government buildings). Facilities that may be crime attractors for robbery may be more or less attractive of firearm-specific robbery depending on whether an offender expects to face armed resistance. The relatively small set of environmental features that have been evaluated as potential risk or protective factors for firearm crimes in prior work limits our understanding of the broader scope of features that may shape spatial patterns of firearm-specific crimes in a jurisdiction.

The rest of this paper is organized as follows. Next, we provide a background of previous literature on built environment and gun violence. In Section "Application to Four U.S. Cities", we describe the *Network Cross-K Function for Stochastic Spatial Events (NKFSSE),* define its key metrics, and present the analytical data. In Section "Results", we present results for four U.S. cities. Finally, we discuss insights from our results and their implications for policymakers, urban planners, and law enforcement.

Background

All places are at risk for crime, but the spatial influence of certain physical features generates greater risk at some places more than others (Kennedy et al. 2016). The importance of micro-places for understanding patterns of spatial crime concentration is theoretically grounded in crime pattern theory (Brantingham and Brantingham 1993; Cohen and Felson 1979) whereby "crime places" (also known as "crime generators" and "crime attractors") influence crime in the surrounding area due to a nonrandom convergence of offenders and targets, and a lack of guardianship in time and space (Wilcox and Cullen 2018). Conversely, "crime detractors" are features that push people away due to

a lack of activity. There are still other locations where numerous people congregate, and yet very little crime occurs. In this work, we say that these features exert a "repellant" influence.

With the exception of a very recent study in Detroit (Oliphant 2021), a study in Little Rock, Arkansas (Drawve et al. 2014), and one focused on Kansas City, MO and Chicago, IL (Barnum et al. 2017), existing research on the built environment and firearm crime has been conducted in a few, select cities in the Northeast including Newark, NJ (Kennedy et al. 2011; Piza and Gilchrist 2018; Xu and Griffiths 2016), Irvington, NJ (Caplan 2011), Baltimore, MD (Szkola et al. 2019), and Philadelphia, PA (Jay 2020). The studies in Newark and Irvington, New Jersey demonstrate that gun violence occurs close to locations of drug arrests, residences of gang members, liquor and grocery stores, retail businesses, residential foreclosures, and public housing (Caplan and Kennedy 2009; Kennedy et al. 2011). The authors find no relationship between gun violence and gas stations, laundry services, fast food restaurants, health care centers, and public middle- and high-schools.

Applying a Network Cross-K Function approach developed by Okabe and Sugihara (2012), Xu and Griffiths (2016) incorporate street networks to quantify the attractive influence of various built environment features on the incidence of shootings in Newark, New Jersey. They find that liquor stores, grocery stores, bus stops, and foreclosures are significant attractors for shootings, whereas gas stations, take-out and fast-food restaurants, laundry or dry-cleaning stores, and middle and high schools do not have a significant relationship with shooting incidence. Barboza (2018) leverage the Cross-K function to public schools in Boston, MA., finding that public schools significantly attracted firearms incidents from 2012–2015 and apply a G-function to evaluate univariate clustering. Oliphant (2021) applies the Network Cross-K function and a G-function to features in Detroit, adding a square root transformation meant to stabilize variance called the Cross-L function. The research uncovers that bus stops and blighted vacant properties attract firearms violence. They also find that alcohol outlets attract firearms violence, but only at night. Finally, the work aligns with Xu and Griffiths (2016) but not Barboza (2018), demonstrating that schools do not attract firearms violence.

There is reason to believe that comparing results from different cities could uncover insights pertaining to why firearm crimes occur where they do. In a multi-city study of risk factors for robbery, Barnum et al. (2017) highlight the potential heterogeneity of place-based risk factors across jurisdictions, both in terms of the extent to which they elevate crime risk as well as the distance over which they exert spatial influence. Some features (e.g., foreclosures, gas stations, grocery stores, bus stops, drug markets, and liquor stores) were risk factors for robbery across three cities, but the distance over which they elevated risk varied. For example, the authors find increased robberies within half of a block of liquor stores in Chicago, IL but within three blocks in Kansas City, MO and Newark, NJ.

With recent works drawing connections between socio-economic status and the propensity for firearms violence, one potential reason for the different results across cities is the socio-economic context. Using county-level information in a national study, Rowhani-Rahbar et al. (2019) demonstrate that income inequality (as measured by the Gini index) is associated with firearm homicides in the U.S. Meanwhile, Kim (2019) identifies specific county-level indicators such as social mobility and income inequality are related to census-tract level firearms homicide rates, non-mass shooting homicide incidents, and combined mass shooting and non-mass shooting homicide incidents. The results of these works indicate that economically poorer parts of a city may be more likely to experience firearms violence. However, none of these works evaluate risk as a function of the distance from built environment features, conditional on socio-economic context.

Methods

This research applies the *Network Cross-K Function for Stochastic Spatial Events (NCF-SSE)*, which measures the extent to which probabilistic events occur near fixed locations. We apply this approach to measure the propensity for firearms violence to occur near built environment features. This work leverages shortest-path network distances instead of planar distance, allowing for increased precision (Xu and Griffiths 2016). Leveraging the actual locations for a given feature (e.g., gas stations), the overarching framework is as follows. First, we compute values for the Network Cross-K function using the actual locations of reported firearms. Then, we perform several iterations of Monte Carlo simulation, where each iteration randomly distributes the same number of firearms incidents across the street network. Finally, we compare the Network Cross-K function values that were computed using actual locations with the range of Cross-K function values generated through Monte Carlo Simulation. This comparison determines whether a significant attractive or repellant influence exists, and the range of distance over which the influence persists. Then, we further explore the relationship in terms of the number of incidents that occurred per unit of distance and socio-economic context.

Formally, we define each street network $S = (N, E)$, where N is a set of nodes that signify intersections, and E is a set of edges that represent street segments. Let l_S be the sum of all the edge lengths in the network. Let A and B be two additional sets of nodes located on S. Each node $a_i \in A$ represents the static location of some physical feature where $n_a = |A|$. Each node $b_j \in B$ represents the location of an incident of firearms violence where $n_b = |B|$. Let d_{ij} be the shortest-path distance between $a_i \in A$ and $b_j \in B$ and let $p_{ij}^t = \begin{cases} 1 & if d_{ij} \leq t \\ 0 & Otherwise \end{cases}$. The Network Cross-K Function is given in Eq. 1.

$$K^{ab}(t) = \frac{l_S}{n_a n_b} \sum_{i=1}^{n_a} \sum_{j=1}^{n_b} p_{ij}^t \tag{1}$$

We leverage this metric to test the Complete Spatial Randomness (CSR) hypothesis, which states that points are identically and independently distributed according to a uniform distribution on the street network (Xu and Griffiths 2016). We test this hypothesis by comparing Network Cross-K values from observed data to Cross-K values from a series of simulations. If the hypothesis holds for the locations of fixed features and firearms incidents, the locations of features are not associated with the locations of firearms incidents. However, if there is an influence, we reject the hypothesis and conclude that firearms incidents do occur more or less frequently near a certain feature than we would expect. To avoid artificially inflating Cross-K values, if a single firearms incident lies within t distance of multiple features, it is only counted once. Thus, $K^{ab}(t)$ is a constant multiple of the cumulative distribution of firearms incidents.

We apply the Network Cross-K Function twice in our analysis. First, we compute $K^{ab}(t)$ on the observed data for physical feature type A (ex. Libraries) and firearms violence locations B for all distance thresholds $t \in T$. Next, the street network and the locations of physical features provide the input for a simulation, which randomly distributes hypothetical firearms incidents.

During each iteration of the simulation, N_b firearms incidents are randomly distributed throughout the network. In order to choose the location for simulated firearms incident node N_s, the simulation first randomly selects an edge e in the network, weighting this selection by the length of the edge. In this way, an edge that is 100 ft long has 10 times

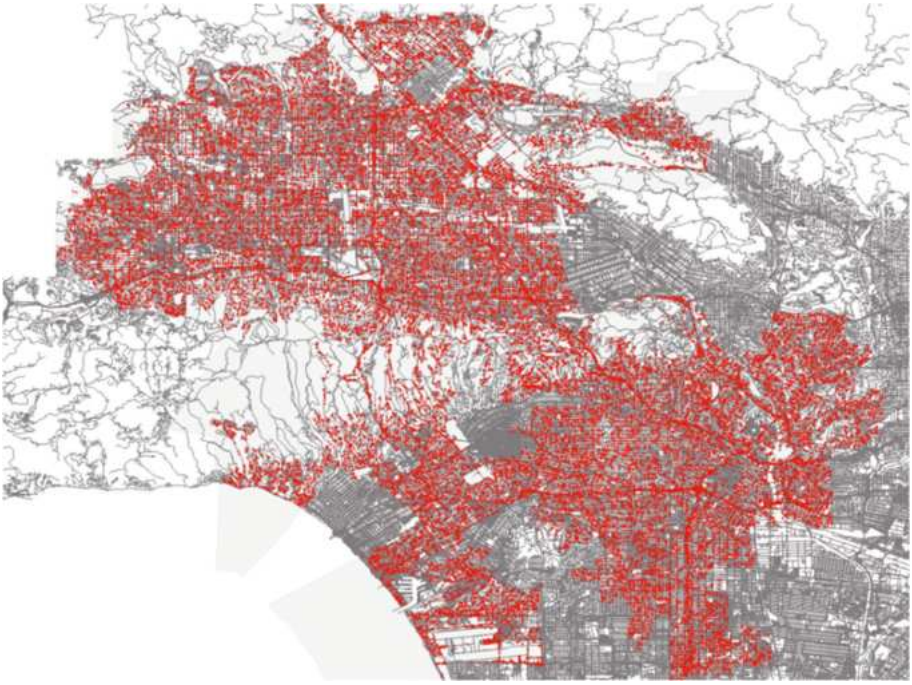

Fig. 1 The output of one simulation on the street network of Los Angeles

the likelihood of being selected than an edge that is 10 ft long. Let $e = (N_1, N_2)$ where N_1 and N_2 represent the nodes at the end points of e, and let the l_e be the length of e. Next, the model randomly generates a number p between 0 and 1, which represents the percent of the way between N_1 and N_2 to locate N_s. Node N_s is created in the network, along with edges $e_1 = \{N_1, N_s\}$ and $e_2 = \{N_s, N_2\}$ where where $l_1 = p * l_e$ and $l_2 = (1 - p) * l_e$. Finally, edge e is deleted from the network. Figure 1 illustrates the output of one simulation iteration on Los Angeles where we can observe a randomized distribution of firearms incidents across the street network. The areas in grey are not within Los Angeles and not a part of our study.

After 200 iterations of Monte Carlo Simulation, we determine whether an attractive/repellant influence exists by comparing $K^{ab}(t)$ from the observed data with $\hat{K}_i^{ab}(t)$ from the simulated data. Ideally, methods of statistical inference would be applied to definitively indicate whether the observed data differs significantly from the simulated data. The Network Cross-K Function is a constant multiple of the cumulative distribution of firearms incidents as a function of distance from features. Therefore, we attempted to apply the Kolmorgorov-Smirnoff test (Massey 1951), to detect a significant attractive or detractive influence. However, our results found extremely low p-values for every feature, indicating that every feature's influence is significant overall. Unfortunately, this finding is rather unhelpful for achieving our objectives.

Therefore, we apply the following decision criteria for determining influence: For some range of distance values $t \in [t_1, t_2]$, If $K^{ab}(t) > \max_i\{\hat{K}_i^{ab}(t)\}$, we reject the CSR and conclude that the physical feature exerts an attractive influence within $[t_1, t_2]$. Alternatively,

For physical feature A and firearms violence location B,

1. On observed data, calculate $d_{ij}\ \forall a_i \in A, b_j \in B$
2. Create distance increments $t \in T$ (eg. 1 ft through 1,000 ft)
3. Compute $K^{ab}(t) \forall t \in T$ on the observed data
4. Run 200 iterations of Monte Carlo Simulation, where each iteration uniformly distributes firearms violence locations $\hat{b}_j \in \hat{B}$
    a. After each iteration *i*, compute Cross-K values $\hat{K}_i^{ab}(t) \forall t \in T$
5. Compare $K^{ab}(t)$ with $\hat{K}_i^{ab}(t)\ t \in T$.
    a. If $K^{ab}(t) > \max_i\left\{\hat{K}_i^{ab}(t)\right\}$, the physical exhibits *attractive influence* at distance *t*.
    b. If $K^{ab}(t) < \min_i\left\{\hat{K}_i^{ab}(t)\right\}$, the feature exhibits *repellant influence* at distance *t*.
    c. If $\min_i\left\{\hat{K}_i^{ab}(t)\right\} < K^{ab}(t) < \max_i\left\{\hat{K}_i^{ab}(t)\right\}$, the feature is *neutral* at *t*.

Fig. 2 Pseudo-code for implementation of the Network Cross-K Function for Stochastic Spatial Events

if $K^{ab}(t) < \min_i\left\{\hat{K}_i^{ab}(t)\right\}$, we also reject the CSR hypothesis and conclude that the physical feature exerts a repellant influence within $[t_1, t_2]$. Finally, if $\min_i\left\{\hat{K}_i^{ab}(t)\right\} < K^{ab}(t) < \max_i\left\{\hat{K}_i^{ab}(t)\right\}$, we fail to reject the CSR hypothesis and conclude that the locations of the physical features present no significant influence on the locations of firearms violence labelling the feature "neutral". This process is summarized with pseudo-code in Fig. 2. We present a hypothetical example for our methods in "Appendix".

We also evaluate the Firearms Incident Density, $S^{ab}(t)$, which represents a measurement of risk as a function of distance from features. This measure counts the number of firearms incidents that occurred within distance t of an average feature, capturing the dissipation of influence with increasing distance (Eq. 2).

$$S^{ab}(t) = \frac{\sum_{i=1}^{n_a}\sum_{j=1}^{n_b} p_{ij}^t}{n_a t} \tag{2}$$

Our framework diverges slightly from (Xu and Griffiths 2016) who exclude n_a from the denominator of $S^{ab}(t)$. We include this component to account for the fact that the number of features of a certain type will have some natural association with the number of proximal firearms incidents. That is to say, given two feature types with similar influence, the feature type with a high number of locations will naturally be near more firearms incidents than a feature type with a small number of locations. Similar to the Cross-K function, if a firearms incident node is within t of multiple features, it is only counted once in the density calculation. To serve as an example, suppose there exists one location ($n_a = 1$) for a particular feature *a*. Suppose further that one firearms incident had occurred at a 250 ft. distance. Then, the firearms incident density reaches its maximum at 250 ft, where $S^{ab}(250) = \frac{1}{1(250)} = 0.004$ and declines as t increases. Had there been two locations for feature a, and the firearms incident occurred near only one of them, then $S^{ab}(250) = \frac{1}{2(250)} = 0.002$, which reflects the fact that fewer firearms incidents occurred *per location*.

To quantify influence dissipation over distance, we perform piecewise linear regression on the firearms incident density for each feature. Breakpoints between segments are determined through Pruned Exact Linear Time (Pelt), a penalized change-point detection

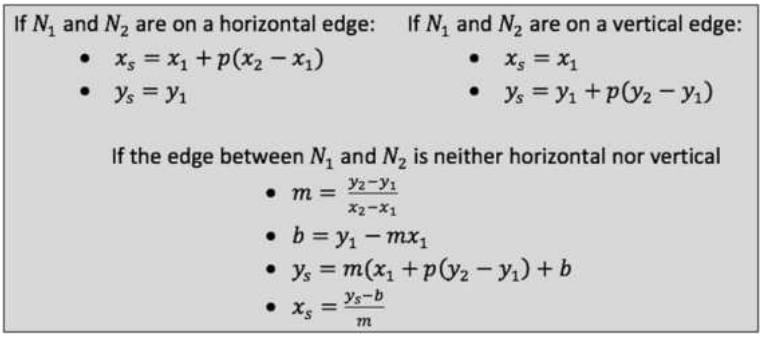

Fig. 3 Linear Interpolation to compute coordinates for simulated firearms incidents

algorithm (Wambui et al. 2015), that identifies statistically significant changes in the pattern of influence. The equation for the regression line-segment between each pair of breakpoints is determined through Ordinary Least Squares (OLS) regression. These regression line segments illustrate how the number of firearms incidents per unit of distance from a feature change as distance increases. For example, a high intercept and negative slope at small values of t, indicates that numerous incidents occur near a feature but decrease as distance increases. Alternatively, a low (even negative) intercept and a small, positive slope indicate that incidents occur further away from the feature.

Our measurements consider only firearms incidents within 1000 ft of features, which corresponds to 1–3 city blocks. Before measuring the shortest path distance, the program measures the Euclidean planar distance between an incident and a feature using their associated latitude and longitude coordinates. If the planar distance is greater than 1000 ft, the shortest-path distance must also be greater than 1000 ft, and the program need not measure the shortest-path distance as it is outside our scope.

Before the simulation can calculate planar distances, each simulated incident node N_s must be assigned latitude (x_s)/longitude (y_s) coordinates. Once a random edge $e = (N_1, N_2)$ is chosen, we perform linear interpolation using the coordinates of N_1, N_2, and p, as depicted in Fig. 3.

Variation in results across cities speaks to the importance of understanding underlying factors, such as socio-economic status (SES), that have been shown drive firearms violence (Mills et al. 2019; Sampson and Groves 1989; Shaw and McKay 1942). To explore the extent to which SES explains or adds depth to our results, we apply the *NCFSSE* to subsets of feature locations according to the socio-economic status of the census tract in which the feature is located. Each census tract is designated a socio-economic index score described in Section "An Index of Socio-Economic Status", based upon the methods of Hunt et al. (n.d.), which incorporates indicators such as median household income, housing vacancies and unemployment from the American Community Survey (U.S. Census Bureau 2018). We compare results for features located in census tracts corresponding to the top and bottom 25th percentile of SES index in each city, analyzing the extent to which results vary from their city-wide presentations. The reader may note that some firearms incident density values for subsets of locations are higher than those for the full set of locations due to a lower number of facilities (n_a) in the denominator.

Table 1 City characteristics from Detroit, Los Angeles, New Orleans, and Pittsburgh

	Detroit	Los Angeles	New Orleans	Pittsburgh
Population, 2014	680,250	3,913,000	384,320	305,412
Land Area (sq. miles)	138.8	469.1	180.6	55.6
Proportion of population living below poverty, 2017	0.345	0.174	0.262	0.202
Police Officers per 10,000 residents	36	25	30	38
Urban Sprawl Index				
Density score	125.20	187.39	104.84	96.16
Land use mix score	124.65	160.18	117.83	115.14
Activity centering score	107.48	115.66	96.09	107.78
Street connectivity score	183.98	154.40	149.94	119.33
Composite	137.17	130.33	119.74	95.45
Ranking (out of 221 metro-areas)	12	21	42	132

Application to Four U.S. Cities

Leveraging parallel processing and cluster computing, the methods described above are applied to four U.S. cities using a computer program written in Python 3.6 programming language. Distances are calculated using the heuristic "A-star" to maintain computational tractability. We focus our study on: Detroit, Los Angeles, New Orleans, and Pittsburgh. These cities were selected because they all suffer from gun violence, but are located in diverse geographic regions and vary in area, population, and available law enforcement resources (City Data 2020a, b, c). Table 1 summarizes some helpful information. In terms of urban environment, all cities score greater than the U.S. median urban sprawl (SGA 2014), yet they differ in terms of built environment and walking culture.

Pittsburgh is the smallest city in our study with regards to population and land area. Detroit is densely populated across most of its space, where over 680,000 residents live within 138.8 sq. miles. New Orleans occupies over three times the area (180.6 sq. miles) of Pittsburgh, though it includes 26% more people than Pittsburgh. Los Angeles is the largest city we analyze by far in both population and land area.

Regarding police presence, Pittsburgh has the highest number of police officers per capita in our study with 38 officers per 10,000 residents, although Detroit has only slight fewer (36 per 10,000). New Orleans maintains about 30 officers per 10,000 residents. Los Angeles has the least number of police officers per capita within our study (25 per 10,000 people), which is 53% less than in Pittsburgh.

From a socio-economic perspective, Detroit is the least prosperous city in our study with the greatest proportion of their population living below the poverty line, approximately one out of three people living in poverty. Approximately one in four people live in poverty in New Orleans, and one in five people live in poverty in Pittsburgh. Los Angeles has the lowest poverty rate with 17.4% living in poverty.

Turning to built environment, a 2014 study by Smart Growth America (SGA) measured sprawl by looking at density of residential and commercial development; the mix of homes, jobs, and services in a community; how centrally located downtown districts and activity centers are; and accessibility of the street network. Of the cities we study, Pittsburgh is far more sprawling than the others. Detroit is the most compact and connected of our

cities, as it is the 12th most compact in the U.S in 2014. New Orleans has the lowest activity centering score, signifying the lowest proportion of residences and businesses located near each other. This may be partially due to restrictions on high-rise buildings that would permit more people to live near business centers. Los Angeles has the second-highest density score in the country, topped only by the New York metro area. Several public policies have contributed to Los Angeles's high development density score, including a plan for development around transit stations, allowing higher density in exchange for affordable housing, and a multi-year process to update its zoning code (SGA 2014). While the methods employed in this paper examine socio-economic context within a geospatial analysis, future work might examine the influence of other city characteristics such as population density and urban sprawl on the locations of firearms violence. Since these variables determine the frequency that individuals cross-paths, there may exist an association with crime that should be explored.

Data Collection

Reported Crimes with a Firearm

Crime datasets are available within each city's open data portal, but the range of years and type of crime reported are not uniform across cities. To identify firearms incidents, we filter reported crime data first by crime type, including all Part 1 crime types of homicide, robbery, aggravated assault; the type of weapon was not available for the crime of rape. We then filter based upon string searches for terms such as "Gun" or "Shooting". All reported firearms crimes are defined using the Uniform Crime Reporting (UCR) hierarchy. We include a broader definition of firearms crime than other research because firearms crime is not limited to offenses where a weapon was discharged but includes instances where an offense was facilitated by a firearm, such as robbery.

For each city, firearms incidents are recorded at the corner of the block as the last two digits of all addresses for firearms incidents are missing. To locate incidents on our network, we imputed "00" as the final two digits. While this may introduce some inaccuracy when measuring the distance between firearms incidents and built environment features, this is restricted to the first block. Second, assigning firearms incidents to the corner is equally likely to increase the distance to features as it is to shorten it and we are aggregating over thousands of measurements. Oliphant (2021) performs sensitivity analysis using similar data in Detroit and demonstrates that recording a proportion of firearms incidents at corners does not impact results.

For Detroit data, we filter for gun crimes by restricting to entries that contained the string "Gun" or "Shooting" in the field "Offense Description." We restrict to incidents that occurred from 2014–2016 and drop entries that are not geocoded or are geocoded incorrectly (971 out of 15,112, or 6.4 percent). Thus, our analytical sample contains 14,141 firearm incidents.

Regarding Los Angeles data, we filter for gun crimes by restricting to entries that contained both a firearm-related term in the "Weapon Description" field and Robbery, Aggravated Assault, Manslaughter, Homicide, or Shots Fired in the field "Crime Code Description." Temporally, we restrict to incidents that occurred in 2013–2017. Then, we drop entries that were incorrectly geocoded (379 out of 29,727, or 1.3 percent). Thus, our analytical sample contained 29,348 firearm incidents.

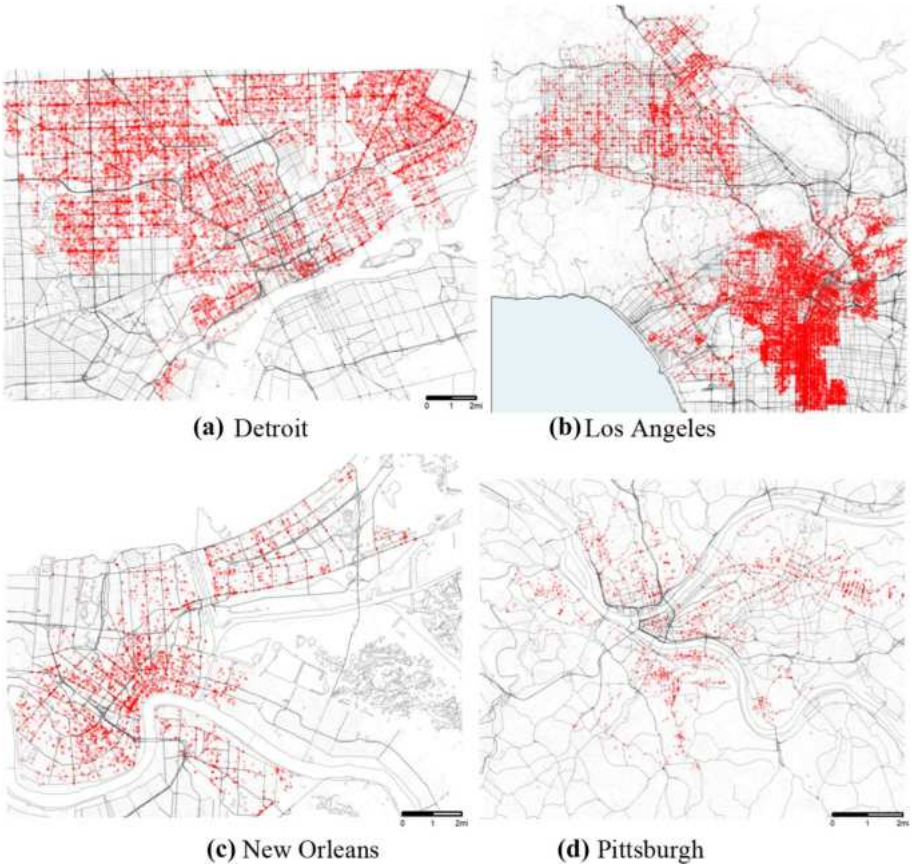

Fig. 4 Spatial distribution of reported crimes with a firearm in **a** Detroit (2014–2016), **b** Los Angeles (2013–2017), **c** New Orleans (2015–2017), and **d** Pittsburgh (2015–2017)

The data for New Orleans requires duplication of the fields "Offender Number" and "Victim Number" so that multiple entries for the same incident are ignored. Then, we filter for gun crimes by restricting to entries that contain the string "Gun" or "Shooting" in the field "Signal Description" and restrict to incidents that occurred from 2013 to 2017. The data is not geocoded, so we input the address for each entry into the R data science toolkit (RDSTK) API.

For Pittsburgh data, we filter for gun crimes by restricting to entries that contained the string "Gun" in the field "Incident Hierarchy Description." We restrict to incidents that occurred in 2016–2018 and drop entries that were not geocoded (294 out of 11,831, or 2.5 percent).

Figure 4 illustrates the spatial distribution of firearms incidents across each city over the study timeframe. One challenge with using street networks concerns features and firearms incidents that are located close to the border of the network. It has been observed that shortest-path distances involving these points may be artificially large due to a lack of paths between firearms incidents and features along the edges of the network. In an effort to mitigate this effect, our street networks include all roads from the entire county in which

a focus city is located. However, when the simulation randomly selects an edge upon which to locate a firearms incident, the program is restricted to choosing edges within the city. In this way, simulated firearms incidents only occur in the city, but shortest paths may utilize all roads within the county.

The advantage of using reported crimes from each city's police department is that there is a systematic process for documenting and categorizing a crime. One weakness of the data may be spatial accuracy, since less precise spatial referencing methods may place crimes in locations where the events do not actually cluster. We are not aware of a bias for any particular feature, so this could affect any of the results. Another potential disadvantage is due to underreporting of firearms violence. This would only affect our results if individuals refrain from reporting firearms violence to the police that are near specific features. Given that our analysis is at the feature level, it is unlikely that underreporting biases results. That is, underreporting would only bias our results if feature locations influence the probability of reporting crime. For underreporting crime to affect relationships, it would require systematic underreporting of crime near some features but not others (e.g., all liquor stores across a city). Research shows there is more underreporting of certain crime types in lower SES neighborhoods. If this trend should influence our SES-related analysis, our results would determine features in these areas are *less* attractive/*more* repellant than they are, as more firearms incidents occurred than were reported. Thus, if our SES results are bias due to underreporting in low-SES areas, these features are even more attractive to firearms crime than we depict.

Built Environment Features

We incorporate a diversified set of geolocated features by obtaining datasets that include the locations of built environment features within the same years as we have firearms data. For each city, we identify a range of years for which both built environment and firearms data exists. While we would have liked to examine the same range of years in each city, a lack of available data made this infeasible. We leverage the datasets that gave a comprehensive listing of the use or vacancy of a building. For locations of transit stations and universities/colleges, we leverage data from Homeland Infrastructure Foundation-Level Data (2020a, 2020b).

For the remainder of features, we leverage each city's open data portal to collect the relevant, geocoded datasets (City of Detroit 2019; City of Los Angeles 2020; City of New Orleans 2015; Allegheny County and the City of Pittsburgh 2020). For each city, Table 2 presents the study years, the number of feature types, and the number of recorded firearms incidents. If located outside of the street network, the location of each feature is snapped to the nearest road segment according to Euclidean distance. All built environment features and firearms incidents are embedded within each city's street network (OpenSreetMap 2022). For transparency, code and supporting data files have been uploaded to RAND's public GitHub.[1]

An Index of Socio-Economic Status

Socioeconomic status (SES) is measured a variety of ways, typically incorporating education, social class, and/or income. This research incorporates an index of SES at the

[1] https://github.com/RANDCorporation/Quantifying-Built-Environment-Influence.

Table 2 Features and Firearms incidents characteristics from Detroit, Los Angeles, New Orleans, and Pittsburgh

	Detroit	Los Angeles	New Orleans	Pittsburgh
Years of analysis	2014–2016	2013–2017	2015–2017	2015–2017
Count of reported crimes with a firearm	14,141	29,348	7656	11,535
Built environment features				
Alcohol venue/Liquor store	891	–	514	–
Convenience stores	–	1061	–	631
Fast food restaurants	–	–	–	631
Gas station	–	–	86	–
Lodging	–	–	316	–
Restaurants	–	–	1106	–
Schools	281	–	115	–
Transit stations	19	57	126	25
Universities/Colleges	10	57	19	33
Tobacco Retailer	–	–	–	427

Table 3 Demographic characteristics for Detroit, Los Angeles, New Orleans, and Pittsburgh presented for the full city, then for lowest and highest quartile census tracts

	Detroit	Los Angeles	New Orleans	Pittsburgh
Median Annual Income ($/year)	$21,085 ($20,990, $40,104)	$23,017 ($18,504, $46,327)	$26,940 (20,625, $41,500)	$30,724 ($16,667, $41,464)
Median Rent ($/month)	$799 ($717, $937)	$1343 ($1,094, $2045)	$980 ($847, 1346)	$873 ($697, $1086)
Percent in Poverty (%)	53% (60%, 41%)	29% (51%, 12%)	38% (58%, 14%)	29% (51%, 21%)
Percent Unemployed (%)	17% (17%, 16%)	7% (9%, 5%)	8% (14%, 4%)	6% (11%, 2%)

census tract-level using indicators such as average annual income, monthly rent, unemployment rate, and percent in poverty between 2014 and 2018 (Census 2018). For each city, all variables were then normalized across census tracts.[2] Finally, we apply Principal Component Analysis (Wold et al. 1987), to combine these normalized variables into a single index. Table 3 presents key demographic information that are incorporated within the SES index for each city. This data is presented for the full city, and then in parentheses for census tracts associated with the lower and upper quartile of SES values, respectively.

Detroit has the lowest median annual income and by far, the highest percent of people in poverty and the highest percent unemployment of the cities in our study. While the median income in poorer areas is higher in Detroit than the other cities, the percent in poverty and

[2] We impute a small number of missing values at the census tract level using Multiplied Imputed Chained Equations (MICE) (Buren and Groothuis-Oudshoorn 2010), taking the median value of 100 imputations. This affects less than ~ 0.5% of observations.

percent unemployed are also higher. Surprisingly, the upper quartile of census tracts also has a median of 41% living in poverty with 16% percent unemployed.

While the median income in Los Angeles is only 9% higher than Detroit, the median rent is 68% larger. In the lower quartile of census tracts, median annual income is $18,504, leaving 51% in poverty, and yet median rent is $1094 per month. Though higher than the other cities, the median income within upper quartile census tracts is only $46,327, where median rent is over $2000 per month. Los Angeles represents the largest disparity between median annual income of individuals in lower and upper quartile census tracts, where the difference is $27,824 per year.

New Orleans has the second highest median annual income, median rent, percent in poverty, and unemployment rate of cities in our study. Despite having lower rent and higher median annual income, New Orleans has a significantly higher percentage of the population living in poverty than Los Angeles, but not as much as Detroit. In the lower quartile census tracts, unemployment is 14% and 58% of people live in poverty. In the upper quartile census tracts, both median annual income ($41,464) and rent ($1346) are second highest, exceeded only by Los Angeles.

Pittsburgh exhibits the highest overall median annual income ($30,724) and the second highest income disparity, with a $24,797 difference between median annual incomes in upper and lower quartile census tracts. In the lower quartile, the median income is only $16,667 and 51% of the population live in poverty. In the upper quartile census tracts, Pittsburgh boasts only 2% unemployment. Yet, 21% of this population lives in poverty, second only to Detroit.

Results

We first present results on transit stations and universities/colleges because we have data for these features in every city. Then, we present results for liquor stores, convenience stores & gas stations, alcohol & tobacco retailers, lodging & food, and schools where data is available. After comparing observed and simulated Cross-K functions to determine attractive, repellant, or insignificant influence, we comment on firearms incident density plots and examine the role of socio-economic context.

Transit Stations

Detroit

Illustrated in Fig. 5 (Panel A), we find that Detroit People Mover (DPM) transit stations exert an insignificant influence within the immediate vicinity, but a repellant influence from 160 to 1000 ft. We observe a spike in incidents at 150 ft wherein 12 incidents are reported (Panel B). There exist nine rail transit stations in Detroit's lowest quartile census tracts. Interestingly, it is these locations that account for most of the crime near transit stations. The maximum incident density occurs at 110 ft (0.008), wherein 8 of the 11 total incidents (72.7 percent) occurred, though these locations only represent 47 percent of the total (Fig. 5, Panel C). Seven of 19 rail transit stations (36 percent) are located in the highest quartile census tracts. The nearest firearms incident to these locations is 200 ft away and the maximum incident density occurs at 655 ft (0.0039), wherein only 30 percent (18

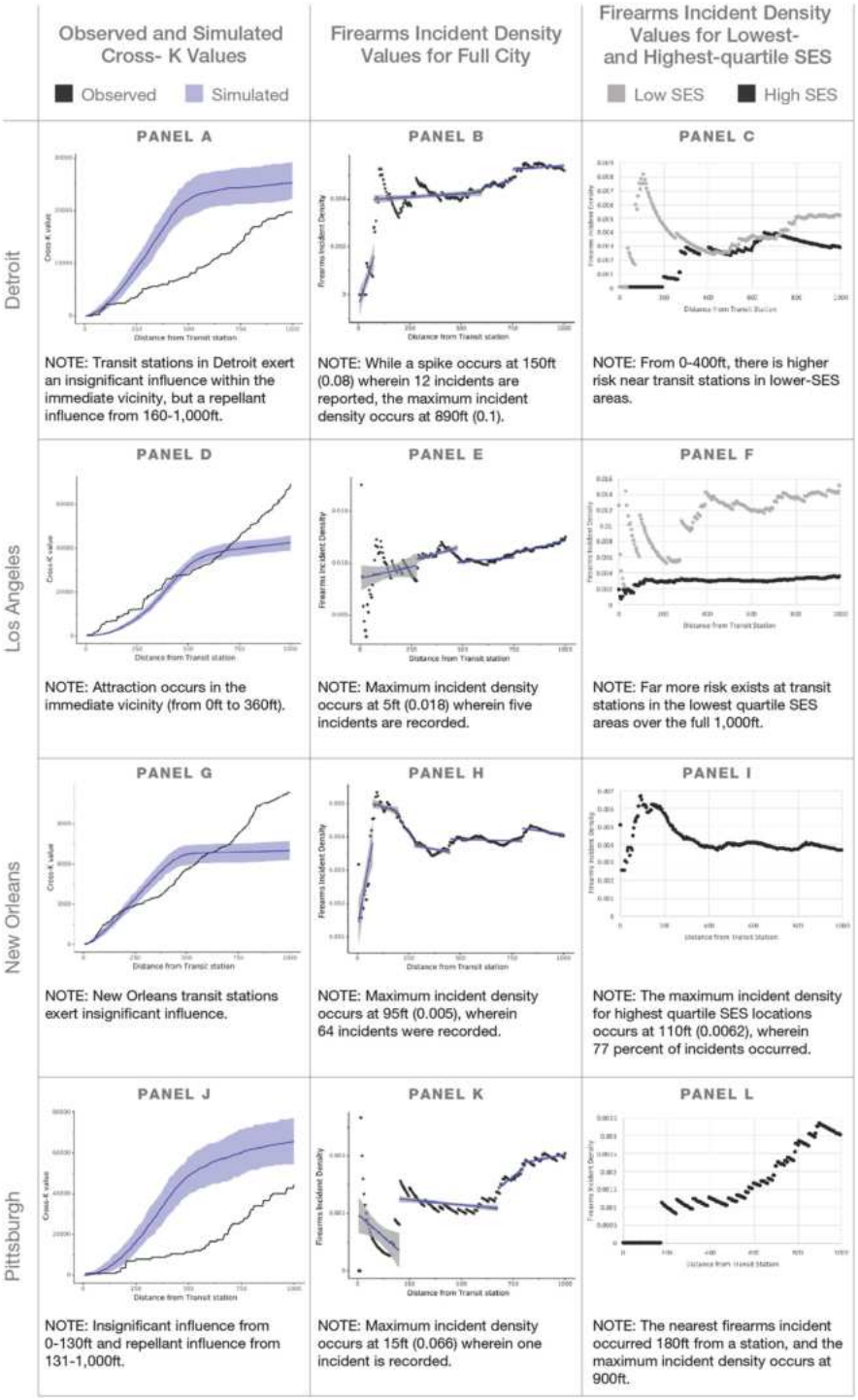

Fig. 5 Resuts pertaining to transit stations

of 59 incidents) occurred. Though transit stations do not attract firearms violence in aggregate, Fig. 5 (Panel C) illustrates that there is more risk near stations in low-SES areas.

Los Angeles

Analyzing locations for Los Angeles County Metropolitan Transportation Authority (LAMCTA) metro rail stations, the greatest attraction occurs in the immediate vicinity (from 0 to 360 ft) and then dissipates as shown in Fig. 5 (Panel D). There is perhaps an interesting volatility along the first segment from 0 to 275 ft, as shown in Panel E. Despite demonstrating an attractive influence, all line segments produced positive slopes, showing the general trend that incident density increases as we move further from the feature. The maximum incident density occurs at the stations (0 ft to 5 ft), where five firearms incidents have been reported within 5 ft of the 57 locations. The minimum value (0.0029) occurs at 35 ft away, as there does not exist another firearms incident between 5 and 35 ft. This may be, in part, because there are no residential or commercial buildings next to metro rail stops. Then, there is a 70 percent increase (from 33 to 56 incidents) from 65 to 80 ft.

Transit stations in the lower quartile SES census tracts in Los Angeles exhibit an attractive influence from 30 to 1000 ft. Eight of 57 transit stations (14 percent) are in the highest SES quartile census tracts and exhibit an attractive influence for the full 1000 ft. While both sets of transit stations are attractive, Panel C illustrates that far more risk exists at transit stations in the lowest quartile SES areas. This differs slightly from the general result throughout where the full set of transit stations were only attractive 0–360 ft.

New Orleans

We find that the full set of 126 New Orleans Regional Transit Authority (NORTA) transit stations exert insignificant influence on reported crimes with a firearm (Fig. 5, Panel G). The maximum incident density occurs at 65 ft wherein 64 incidents are recorded (Panel H). New Orleans has no transit stations located in its lowest quartile census tracts; only in the highest three quartiles. When we focus on the 79 locations in the highest quartile SES areas, we see that transit stations are strongly attractive over the full 1000 ft. Therefore, we expect that the remaining 57 of 126 stations have insignificant or repellant influence on firearm violence. The maximum incident density for highest quartile SES locations occurs at 110 ft (0.0062), wherein 54 out of 70 (77 percent) of incidents occurred (Fig. 5, Panel I).

Pittsburgh

We find that Port Authority of Alleghany County light rail (or "T") stops, are primarily repellants (130–1000 ft), but not significantly from 0 to 125 ft (Fig. 5, Panel J). Maximum incident density occurs at 15 ft (0.066) wherein one incident is recorded (Panel K). Pittsburgh has no transit stations in the lower quartile SES census tracts. Therefore, the main result describes the upper three quartiles of the SES distribution. Focusing upon 10 locations in the highest quartile census tracts, Fig. 5 (Panel L) illustrates that the nearest firearms incident occurred 180 ft from a station, and the maximum incident density occurs at 900 ft wherein 30 incidents were reported.

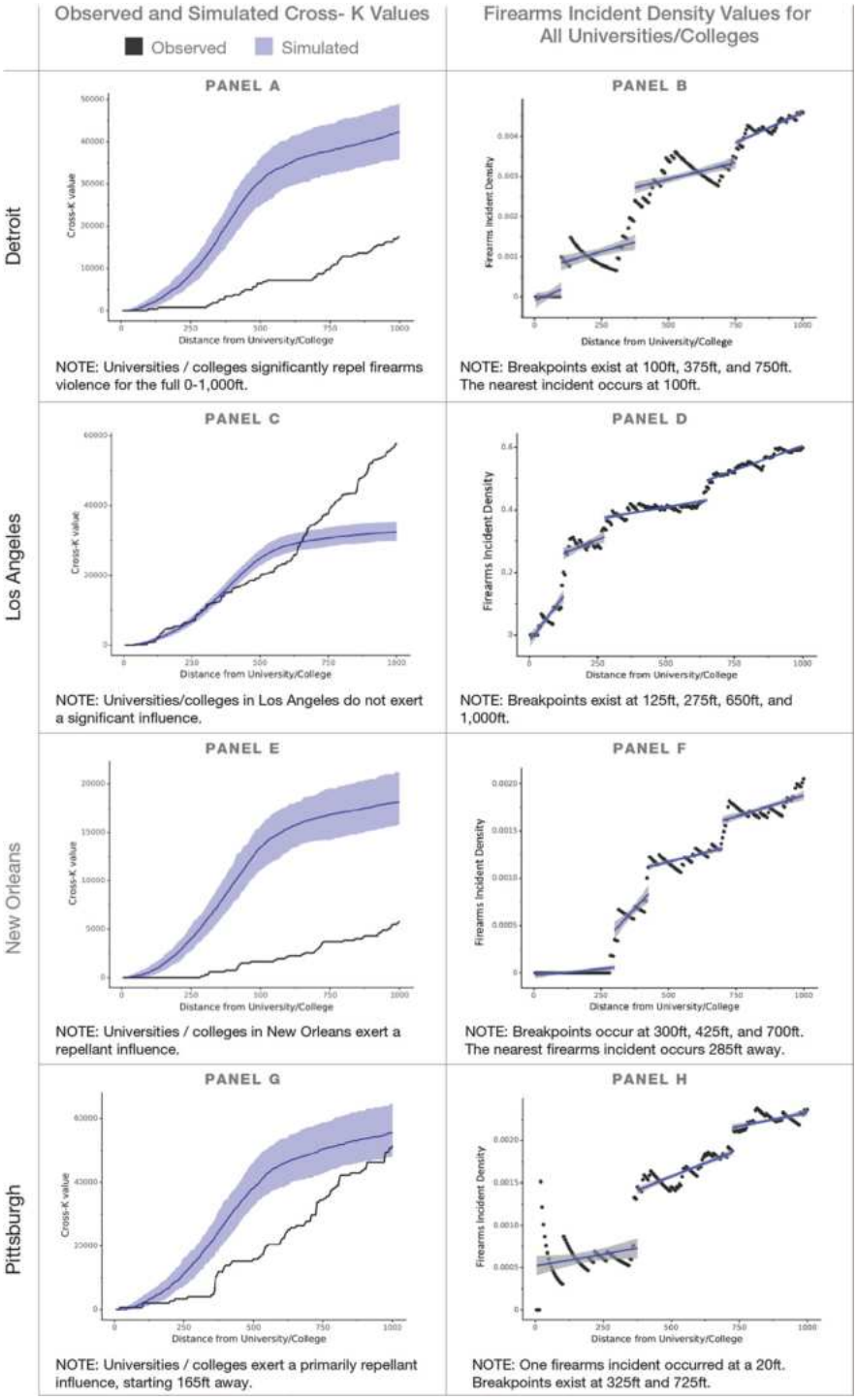

Fig. 6 Results pertaining to universities/colleges

Universities/Colleges

Detroit

Detroit universities/colleges significantly repel firearms violence for the full 0–1000 ft as illustrated in Fig. 6 (Panel A). Firearms incident density patterns for universities/colleges are illustrated in Panel B, where the nearest reported incident to one of the 10 universities/colleges is 100 ft. The maximum incident density values for these features occur at 1000 ft, where the greatest amount of the network is captured.

Los Angeles

Our results indicate that the 57 university/college locations in Los Angeles do not exert a significant influence on firearms incidents. Figure 6 (Panel C) illustrates that observed and simulated Cross-K values are very similar from 0 to 420 ft, after which they deviate, but not in a discernable pattern. The observer will note that these locations appear to be attractive from 705–1000 ft, but we would suggest that this is a result of the surrounding neighborhoods, and not the universities/colleges themselves. Breakpoints in incident density exist at 125 ft, 275 ft, 650 ft, and 1000 ft (Panel D).

New Orleans

Universities and colleges in New Orleans exert a distinctly repellant influence on firearm violence (Fig. 6, Panel E). Exploring these patterns in more depth in Panel B, the nearest firearms incident to the 19 universities/colleges locations does not occur until 285 ft away (Panel F). The maximum incident density values for these features occur at 1000 ft, where the greatest amount of the network is captured.

Pittsburgh

We find that the 33 University/College locations in our data exert a primarily repellant influence, though not until 165 ft away (Fig. 6, Panel G). One firearms incident occurred at a 20 ft distance, creating a steep descent at the beginning of the incident density plot (Panel H), which then increases in three segments with breakpoints at 325 ft and 725 ft.

Convenience Stores & Gas Stations

Los Angeles: Convenience Stores & Supermarkets

The full set of convenience stores and supermarkets in Los Angeles includes 1061 locations. The large number of locations, combined with the large number of reported firearms incidents in the full set proved too computationally difficult to obtain simulation results. However, we were able to perform our analysis for locations in low- and high-SES quartiles, where we find that both are strongly attractive over the full distance

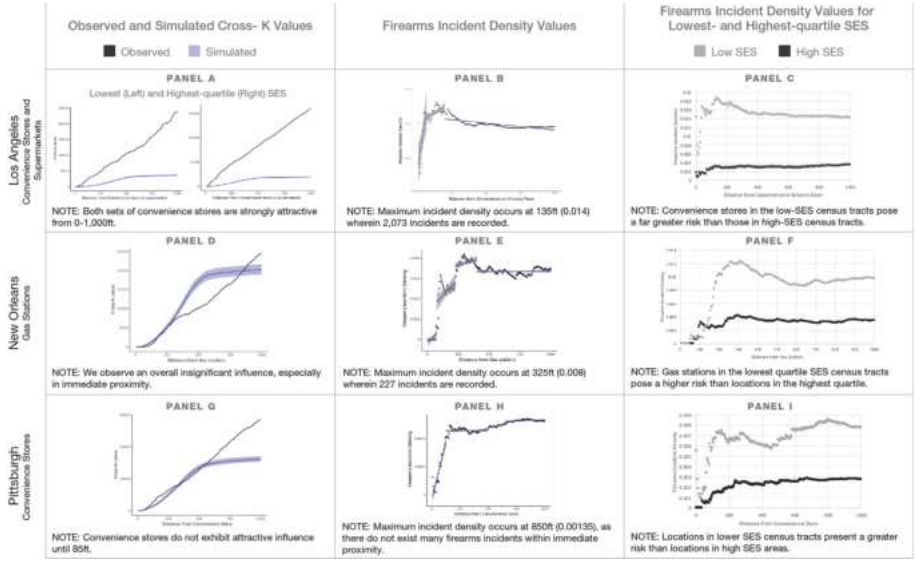

Fig. 7 Results pertaining to convenience stores and gas stations

range (Fig. 7, Panel A). Maximum incident density for the full set of convenience stores occurs at 135 ft (0.014) wherein 2073 incidents are recorded (Panel B).

Out of 1061 convenience stores or supermarkets in Los Angeles, there are 517 locations in lower quartile SES census tracts, representing 48.7% of the total locations. The maximum incident density for these locations occurs at 45 ft (0.017), wherein 414 out of 633 (65.4%) total incidents occurred. The 117 convenience stores in highest quartile census tracts account for 11% of the total locations. Only 2.4% of the incidents within 125 ft of convenience stores were near high-SES locations. Figure 7 (Panel C) illustrates that convenience stores in the low-SES census tracts pose a far greater risk than those in high-SES census tracts.

New Orleans: Gas Stations

Finally, we find reported firearm crimes are unrelated to the location of gas stations in the immediate vicinity, and somewhat repellant from 300 to 800 ft (Fig. 7, Panel D). This was rather unexpected as we anticipated gas stations might be attractors, particularly for robberies with a firearm. Maximum incident density occurs at 325 ft (0.008) wherein 227 incidents are recorded (Panel E). We then consider whether the socio-economic context might influence the relationship between gas station locations and reported crimes with a firearm. We find that gas stations in the lowest quartile SES census tracts pose a higher risk than locations in the highest quartile. In New Orleans, lower quartile census tracts include 30 gas stations, representing 34.9 percent of total locations. The maximum incident density occurs at 305 ft (0.012), wherein 112 out of 205 total incidents (54.6 percent) were recorded at this distance (Fig. 7, Panel F). In New Orleans, 21 out of 86 gas stations are located in the highest SES quartile census tracts. For these locations, the maximum incident density exists at 280 ft (0.0041), wherein 24 incidents occurred. On average, this translates to 1.14 firearms incidents within 280 ft of each gas station in these higher SES

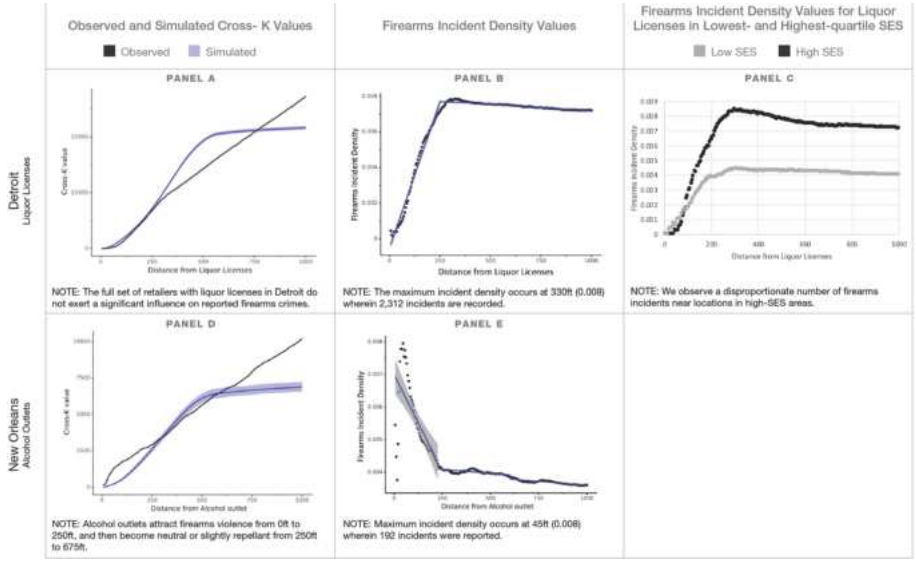

Fig. 8 Results pertaining to liquor licenses and alcohol outlets

areas. Therefore, the general result in Panel A, which illustrates a repellant influence from 300–800 ft, is driven more by gas stations in the higher SES census tracts than in the lower.

Pittsburgh: Convenience Stores

Convenience stores and tobacco retailers exert attractive influence in Pittsburgh. While these features are found to be attractive over similar distance ranges (Figs. 7, Panel G and 9, Panel A) illustrates that the density of firearms violence differs significantly over these same distances. Convenience stores do not exhibit attractive influence until 85 ft, and the overall maximum incident density does not occur until 850 ft (0.00135), wherein there was a total of 727 firearms incidents. The incident density values begin low (0.0003), as there do not exist many firearms incidents near the 631 locations. However, these values increase (Slope = 8.213e−06) until 125 ft. A local maximum equal to 0.0012 occurs at 170 ft (Fig. 7, Panel H).

While convenience stores are only moderate attractors of firearm violence in general, we see that there exist substantial differences in this relationship between the lowest and highest socio-economic areas of the city (Fig. 7, Panel I). There are 36 locations of convenience stores in the lowest quartile census tracts, representing 5.7 percent of the total locations. These locations present a much greater risk than the locations in high SES census tracts. The maximum incident density occurs at 155 ft distance (0.0075), wherein 42 incidents occurred, which represents 35 percent of the total incidents at this distance.

Alcohol and Tobacco Sales

Detroit: Liquor Licenses

In agreement with Oliphant (2021), we find that the full set of retailers with liquor licenses in Detroit do not seem to exert a significant influence on reported crimes involving a firearm. Figure 8 (Panel A) illustrates that reported firearm incidents did not significantly vary from simulated incidents from 0 to 250 ft, and surprisingly become somewhat repellant from 250 to 750 ft. Maximum incident density occurs at 330 ft (0.008) wherein 2312 incidents are recorded (Panel B).

To further examine this result, we evaluate the extent to which socio-economic context impacts the attractive/repellant influence of these features. We find that the locations in both the lowest- and highest-SES areas are strongly attractive, though still not in the immediate vicinity. Locations in the lowest-quartile census tracts are attractive from 40 to 1000 ft. where the maximum incident density occurs at 300 ft (0.0044), wherein 435 out of a total 2092 incidents occurred (20.7 percent). Of the 891 liquor licenses in Detroit, 187 are located within the highest quartile SES census tracts (21 percent), and 329 businesses with liquor licenses are located in the lower quartile of SES census tracts (37 percent). Results show these businesses in high-SES neighborhoods exhibit no significant influence until 75 ft, before becoming very attractive from 75 to 1000 ft. We observe a disproportionate number of firearms incidents near locations in high-SES areas (Fig. 8, Panel C). For the highest quartile SES areas, the maximum incident density occurs at 300 ft (0.0084), wherein 472 incidents occurred, representing 22.6 percent of the total incidents at this distance.

New Orleans: Alcohol Outlets

In New Orleans, we find alcohol outlets, including bars, lounges, and liquor stores, exert attractive influence upon firearm violence within their immediate proximity, a finding consistent with the literature. In Fig. 8 (Panel D), we find that alcohol outlets attract firearms violence from 0 to 250 ft, and then become neutral or slightly repellant from 250 to 675 ft. This latter result suggests that the areas surrounding, but not in the immediate vicinity of, alcohol outlets are not particularly attractive. In addition, the areas much further out from alcohol outlets, from 675 to 1000 ft, are attractive for reports of firearm violence. This may be the result of broader neighborhood characteristics. Figure 8 (Panel E) illustrates that firearm crime occurred very near alcohol outlets, with 23 firearms incidents recorded within 10 ft of alcohol outlets.

Pittsburgh: Tobacco Retailers

Figure 9 (Panel A) illustrates that tobacco retailers are attractors from 0 to 395 ft and Panel B shows that most of the reported firearm crimes occurs at or very near the stores. In fact, we observe a total of 14 incidents within 5 ft of the 427 tobacco retailers. The maximum incident density occurs at 5 ft (0.0065) with three breakpoints at 150 ft, 400 ft, and 850 ft (Panel B).

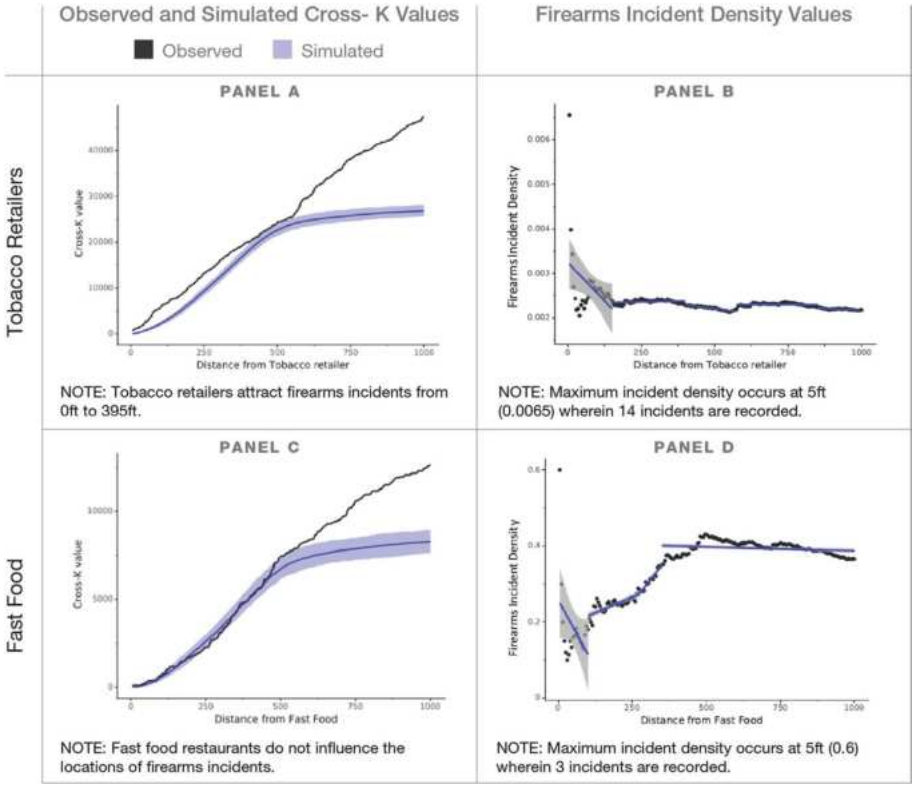

Fig. 9 Results from Pittsburgh pertaining to tobacco retailers and fast food locations

Lodging and Food

New Orleans: Lodging

Lodging, which includes hotels, motels, hostels, and bed & breakfasts, is one of the strongest attractors in our study and the only one that exerts attractive influence throughout the full 0–1000 ft (Fig. 10, Panel A). There were four firearms incidents within 5 ft of the 316 lodging locations and 142 incidents within 75 ft (density of 0.006). The substantial increase in incidents from six with 20 ft to18 incidents within 25 ft is partially responsible for a large, positive slope in the first segment (5.474e−05) (Fig. 10, Panel B). Segments between [110, 525 ft] and [525, 700 ft] have negative slopes as the number of firearms incidents per unit of distance dissipates with greater distances.

New Orleans: Restaurants

Restaurants show a strikingly similar pattern to alcohol outlets (Fig. 10, Panel C), where 1106 locations exert an attractive influence from 60 to 240 ft and 660–1000 ft, but are neutral/repellant from 240 to 660 ft. The associated firearms incident density

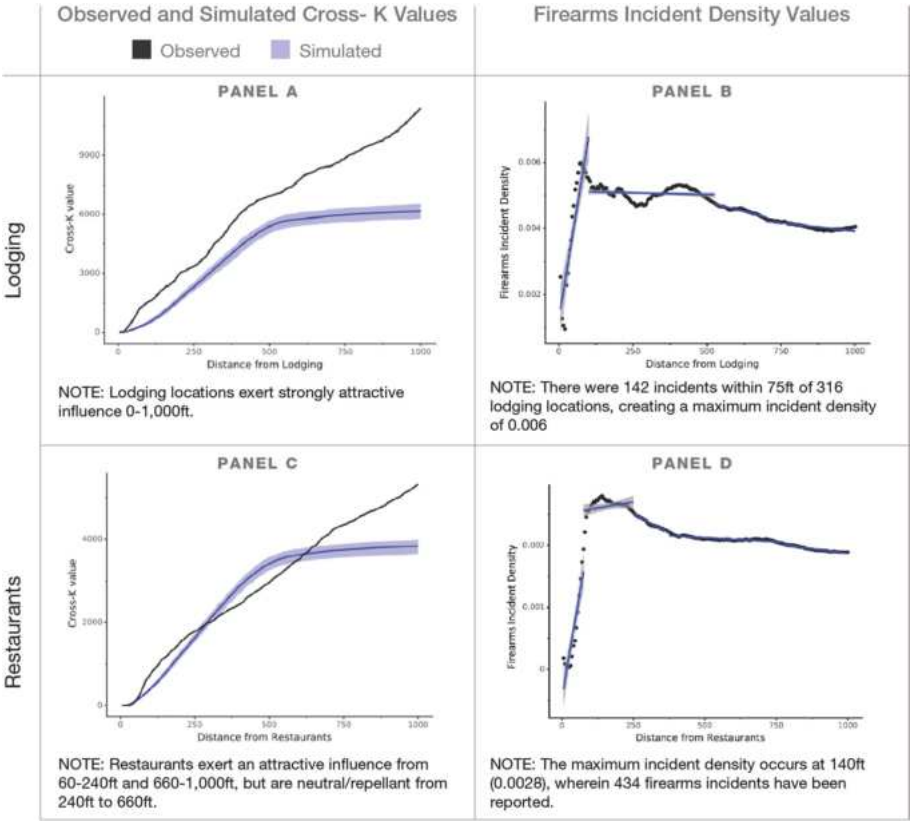

Fig. 10 Results from New Orleans pertaining to lodging and restaurant locations

values in Fig. 10 (Panel D) begin small and increase quickly along the first segment [0, 75 ft], with a slope equal to 2.705e−05. The maximum incident density occurs at 140 ft (0.0028), wherein 434 firearms incidents have been reported. The second segment extends from [75, 250] at a lesser positive slope equal to 7.788e−07. The remaining segments [250,375], [375,775], and [775, 1000] all have slightly negative slopes as the influence dissipates with increasing distance.

Pittsburgh: Fast Food

We find no relationship between the locations of fast-food restaurants and reported firearm crimes in Pittsburgh. Figure 9 (Panel C) illustrates that the observed Cross-K values are very near simulated values. Observed Cross-K values only exceed simulated values (attractive influence) at large distances, from 565 to 1000 ft. This does not necessarily signify that fast-food restaurant have an especially strong influence at these distances. Instead, patterns that emerge at these distances result from characteristics of the surrounding area in which fast-food restaurants exist.

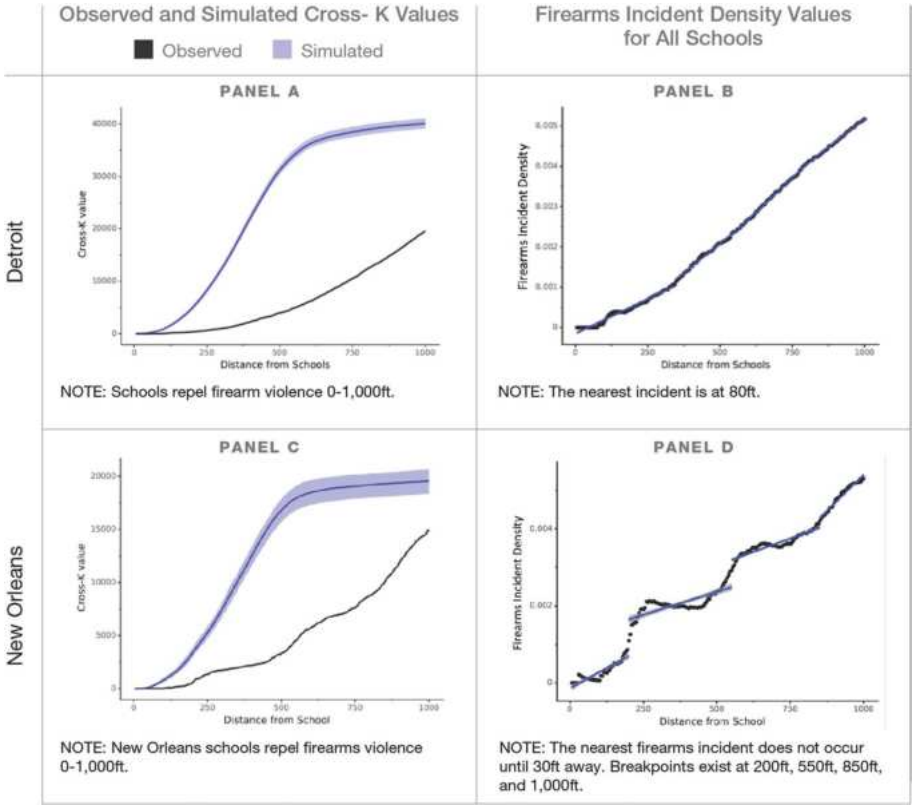

Fig. 11 Results pertaining to Schools

Schools

Detroit

Similar to transit stations and colleges/universities, Fig. 11 (Panel A) illustrates that schools repel firearm violence for the full 0–1000 ft of our analysis. Panel B illustrates the nearest incident to one of the 281 schools is at 80 ft.

New Orleans

In New Orleans, we find that the collection of 155 schools repel firearms violence 0–1000 ft (Fig. 11, Panel C), where the nearest firearms incident does not occur until 30 ft away. The firearms incident density values are broken into four increasing segments with intermediate breakpoints at 200 ft, 550 ft, and 850 ft (Panel D). The stair-step shape of the incident density chart suggests specific distances at which firearms incidents occurred.

Discussion

This research analyzes relationships between firearm crime and ten built environment features in Detroit, New Orleans, Los Angeles, and Pittsburgh. We find that transit stations are attractive in Los Angeles and New Orleans, but repellant in Detroit and Pittsburgh. The attractiveness of metro stations in Los Angeles is greater in the lower socio-economic areas, whereas attractiveness in New Orleans occurs in higher socio-economic areas. Detroit is more like Los Angeles in this respect as the metro stations in the lowest quartile census tracts attract firearm violence; however, because most the stations are in higher SES areas and those repel firearm violence, the general result for the city is that transit stations repel firearm violence. Pittsburgh is unlike that of Los Angeles or Detroit as transit stations repel firearm violence but are only located in middle and lower SES areas.

Concerning the drivers of transit station attractivity in Los Angeles and New Orleans, we reflect on the study of high-crime bus stops in Los Angeles (Levine et al. 1986). The study included observations of social behavior around three street intersections that are high in bus stop crimes, finding that the reason for crime at each bus stop varied. One bus stop was near an open-air drug market, which sometimes led to reported criminal activity. Another bus stop was full of people on sidewalks experiencing theft. And the third was near a high school and a substantial elderly population who were experiencing theft and assaults. Perhaps a general point is that the confluence of people was associated with crime at bus stops. Yet, because the social context varied, no single policy prescription would address all three locations. Oliphant (2021) draws the same conclusions concerning need to contextualize the attractivity of bus stops in Detroit.

We can explore our results in terms of distances and socio-economic contexts to better understand what may be happening. In Los Angeles and New Orleans, the greatest attraction occurs in the immediate vicinity of metro rail stations and then dissipates. Further, firearm violence occurs much closer to transit stations in the lowest SES areas of Los Angeles than in the highest quartile SES areas. We might expect the lower SES areas have relatively more adverse environments as well as more targets sitting and waiting leading to more firearm violent crime at transit stations (Barker et al. 1993; Smith and Clarke 2000). Los Angeles is very dense, and like bus stops, transit stations present opportunities for crime by bringing together potential criminals and targets. In which case, strategies for increasing awareness for potential targets and increasing guardianship in the form of transit police, shot-spotters, salient cameras, etc. may be more appropriate. Despite having the lowest number of police officers per capita of cities in our study, Los Angeles metro stations are patrolled by the Los Angeles and Long Beach police departments, in addition to the Los Angeles Sherriff's Department. The Metropolitan Transportation Authority recently approved a $75 million contract to extend a focused police presence at metro stations (Rasmussen 2021). It is possible that increasing presence at metro stations in lower-SES areas may prevent future violence.

We had discussions with Los Angeles urban planners who raised the issue of blight around transit stations, even in high SES areas. This aligns with more of a "broken windows" explanation (Wilson and Kelling 1982) or a lack of civility on streets and sidewalks creating crime problems (Jacobs 1961). The concept is that an environment with loitering, abandoned buildings, and broken windows, for example, signals suitability for criminal activity. This would mean that the transit stations in low SES areas need to focus on repairing or tearing down blighted or vacant/abandoned buildings, removing vegetation overgrowth, fixing or adding sidewalks, and increasing security through transit policing or

cameras around the stations. While beyond our scope, time of day may play a role in our findings, as security and ridership changes between day and night.

In New Orleans, firearms violence occurs around transit stations in the highest-SES areas. Motivated offenders may use public transportation to prey upon commuters and/or tourists. Therefore, city planners might want to also consider the design elements in the highest quartile SES areas that would help improve safety around transit stations. While urban planners focus on increasing ridership and supporting areas with demand for transportation (Vuchic 2005), the confluence of people and transitory nature can make crime deterrence a challenge. Design characteristics, management practices, and maintenance policies that incorporate principles of situational crime prevention and crime prevention through environmental design (CPED) may be particularly helpful for higher SES areas in New Orleans (La Vigne 2015). For example, there is strong literature on the benefits of street lighting in reducing serious crimes (Chalfin et al. 2021).

As for why universities/colleges repel reported crimes with a firearm in all cities but Los Angeles, we explore the environment and social context of these institutions in each of the cities. First, many universities operate their own police departments, and research shows university police departments can reduce violent crime in particular (Heaton et al. 2016). A search shows that all universities in our study operate campus police departments. Second, student populations may be unsuitable targets and offenders of firearm violence, while targets and offenders of crime in general. A geospatial analysis of arrests surrounding a university in the southeast provides some support for this explanation (Nobles et al. 2010). The study shows that few arrests occur on campus grounds; those that do tend to be concentrated near student bars. As we might expect, students are arrested for crimes next to campus and downtown. Non-student arrest distributions are not correlated with campus locations. Third, this finding may be due to development around universities/colleges. Universities tend to co-locate with typical crime attractors such as bars and restaurants, but they may also co-locate with repellants, such as libraries or schools.

Table 3 summarizes results for features where data availability was inconsistent across cities. In Pittsburgh, convenience stores and tobacco retailers are attractors of firearm violence. We find that convenience stores in Pittsburgh's lowest SES areas attract more firearms violence than those in high SES areas. Pittsburgh's sprawling nature signifies a lower confluence of people than our other cities. However, convenience stores represent a feature that attracts predator and prey, in addition to other types of crime (drug use, etc.). Pittsburgh's relatively large police force may consider increasing presence at convenience stores in lower SES census tracts. While there were too many convenience and grocery stores in Los Angeles to analyze a general result, we were able to compare results for those in the low- and high-SES areas. We found they were also attractors, although convenience stores in the low-SES census tracts pose greater risk for firearm violence. Research shows high sales volume convenience stores are associated with more crime, so this may be driven by a large confluence of people and opportunities for robbery (Askey et al. 2017). One potential strategy would be to explore the extent to which stores are following the principles of CPED—natural access control, natural surveillance, territorial reinforcement, maintenance and management (Crowe and Fennelly 2013)—and Situational Crime Prevention techniques (Clarke 1995). Specifically, research suggests many stores are not in compliance with CPED guidance (Chaumont Menendez et al. 2016). Yet, robbery reductions, for example, are achievable using CPED interventions focusing on basic store design, cash control, and training components (Casteel and Peek-Asa 2000). Given stores in these areas may earn low profit margins and find CPED too costly, a targeted strategy might be

Table 4 Features and firearms incidents characteristics from Detroit, Los Angeles, New Orleans, and Pittsburgh

Built environment features	Detroit	Los Angeles	New Orleans	Pittsburgh
Rail transit stations	−	+	+	−
Universities/Colleges	−	0	−	−
Alcohol venue/Liquor store	0	.	+	.
Convenience stores	.	.	.	+
Fast-food restaurants	.	.	.	0
Gas stations	.	.	−	.
Lodging	.	.	+	.
Restaurants	.	.	+	.
Schools	−	.	−	.
Tobacco retailers	.	.	.	+

"+" signifies an attractive influence, "0" indicates no influence, and "−" signifies a repellent influence. Missing is denoted by a period. Features in italics indicate results exist for all four cities

to encourage or incentivize high sales volume convenience stores in lower SES areas to implement these types of interventions.

In New Orleans, lodging locations are strong attractors of firearms violence. Hotels are a particularly vulnerable location for tourists, unfamiliar with their surroundings, who reveal valuables in public or leave their hotel room door open (Wolff 1993). Therefore, hotel management companies could also engage in more CPTED interventions focused on hotel design and employee training as well as security strategies to reduce the likelihood of firearm violence at their hotels. We also find that alcohol venues (bars, lounges, and liquor stores) and restaurants (that may or may not have a license to distribute) are attractors in New Orleans, although firearms incidents occur closer to alcohol venues. This could be because people consume greater amounts of alcohol at bars and lounges than restaurants. It is possible that tourism and the French Quarter contributes to this violence, as there is evidence that tourists are more likely to be targeted than locals (Eilat and Einav 2004; Michalko 2004; Yang and Hua 2020), especially for property-related crimes such as robbery (Pizam 1999). On the other hand, these tourist areas are often extensively patrolled by police. Lastly, although the overall finding for gas stations in New Orleans is repellant, more firearms violence occurs near gas stations in low-SES neighborhoods than high. Again, this speaks to the finding that high sales volume stores may be at greater risk. Further research could study whether introducing cash control measures with high salience at these type of gas stations can be effective in reducing firearm violence.

In Detroit, results indicate that businesses with liquor licenses (e.g., liquor stores, restaurants) do not attract firearm violence, aligning with Oliphant (2021), who found that attraction only exists at night. Because locations distributing alcohol tend to be associated with crime or public disorder, we explored differences by SES even though the overall result was statistically insignificant. We find liquor license locations in both the lowest- and highest-SES areas are attractive, though not in the immediate vicinity (within 75 feet) and there are substantially more incidents of reported firearm violence near liquor license locations in high-SES neighborhoods. We might expect the locations of liquor licenses in high-SES neighborhoods have more guardians (e.g., private security, police, working cameras) and fewer likely offenders (e.g., opposing gang members at clubs), so this may be due

to more targets with wealth driving firearm-related robberies. Another implication is that there is less firearm violence near the locations in middle SES neighborhoods; therefore, it would be valuable to identify potential risk factors that could be addressed in the high-SES areas of Detroit. We also find that schools repel firearms violence in Detroit, which aligns with Oliphant (2021), but not with Barboza (2018) in Boston (Table 4).

Limitations

While the methods applied in this work are grounded in sound mathematical theory, there are limitations. Our research leverages administrative data, taken from authoritative, publicly available sources. While not created explicitly for research purposes, these data offer a diverse collection of built environment features and are regularly leveraged for a wide variety of official uses, including health department inspections, facilities management, licensing, and land zoning. For example, transit station and university/college locations data were taken from Homeland Infrastructure Foundation-Level Data (HIFLD) Subcommittee Online Community, which was specifically established to improve the collection and sharing of geospatial data across multiple levels of government.

Our methods do not explicitly address temporal changes in the locations of built environment features or firearms violence, nor repeat and near-repeat offenses (Garnier et al. 2018). While the results from a single year may be anomalous, using multiple years of firearms data will capture broader trends. Oliphant (2021) leverages firearms data for only 2020 and notes this as a limitation of the work. This work leverages a range of years for each city (3–4 years) to capture these trends. Given that each experiment leverages a single year of built environment locations, but multiple years of firearms data, we implicitly assume that each feature remains static for study period. It is possible that the opening and closing of businesses during the study period could affect results. However, businesses that inhabit the same location one after another are often of the same type. To impact our results, a large number of features would need to transform into a new type of business within the study period.

Our study does not address any effects of co-locating built environment features. For instance, there may exist areas of a city where several restaurants are located near each other. It is possible that this co-location plays a role in determining the propensity for proximal firearms violence. However, our methods do not capture this influence. This is another reason we focus on transit stations and universities/colleges in the main body of this study; transit stations are not co-located with other transit stations, neither are universities. Future research might incorporate clustering algorithms to measure the extent to which built environment is co-located, and how this affects nearby crime. This type of approach could be extended to analyze interactivity of co-located features from different categories. For instance, we might evaluate how the attractivity of transit stations changes when they are co-located with universities.

We find more features exhibit repellant influence than attractive influence in all cities. One suggested cause is that our networks include space where firearms violence simply does not occur. For example, our network includes segments of interstates and highways. One potential solution is to exclude from the simulation sections of the network where firearms incidents simply do not occur. However, this requires making very large assumptions regarding where firearms incidents can and cannot occur.

We limit both actual and simulated firearms incidents to within city borders. For built environment features located within 1000 ft of a city border, it is possible that firearms

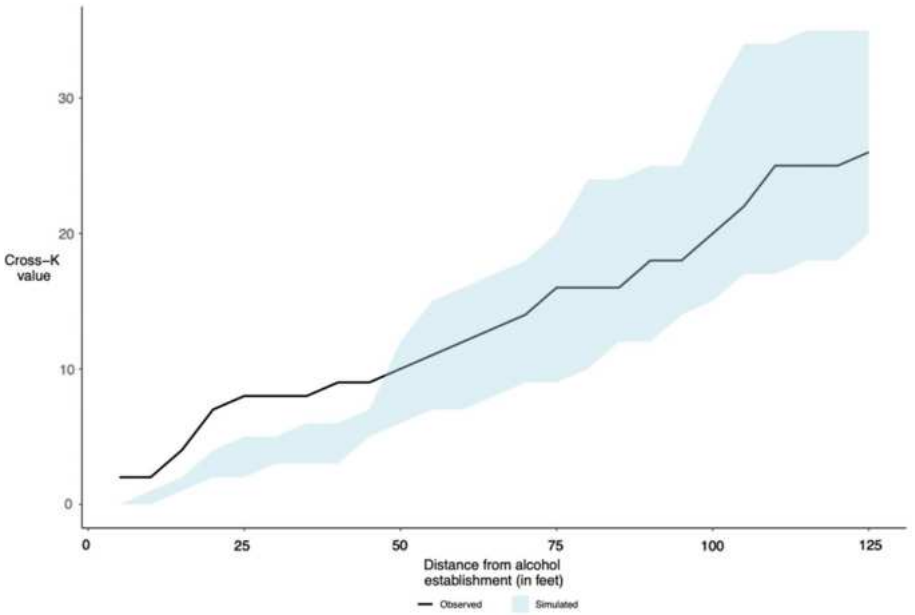

Fig. 12 Example of comparison between observed and simulated cross-K values

incidents occurred immediately across the border and are not counted. This is particularly true in Los Angeles, where many of the neighboring cities are dense and urban. On the other hand, it is equally likely that there are also other features located on the other side of these borders. Unfortunately, it was not possible to collect firearms data for every neighboring area of the cities in our study.

The variance in results across cities indicates that further research should be done to find new ways to measure other drivers of crime so that they can be incorporated into a model. Law enforcement in study cities can discuss our results within the context of their respective jurisdictions, compare results with those of local Shot Spotter, and consider modifying patrols to account for attractive features. Furthermore, policymakers should consider the attractive and repellant influences of built environment features when selecting new locations for development.

Appendix: A Hypothetical Example of the Network Cross-K function for Stochastic Spatial Events

Suppose there exist two alcohol establishments on a street network where the cumulative edge weight equal to 1000 ft. Suppose further that out of a total 50 firearms incidents, seven of them occurred within 20 ft of these restaurants, and a total 20 firearms incidents occurred within 100 ft of these restaurants.

We run 200 iterations of Monte Carlo Simulation, where each iteration randomly distributes 50 firearms incidents across the network. Suppose that, at a distance of 20 ft, the minimum number of simulated incidents across all iterations is two and that the

maximum is four. Finally, suppose the minimum and maximum number of simulated firearms incidents at 100 ft distance are 15 and 30, respectively.

At 20 ft distance, we compute $K^{ab}(20) = \frac{1,000}{(2)(50)}(7) = 70$, $\min_i\{\hat{K}_i^{ab}(20)\} = \frac{1,000}{(2)(50)}(2) = 20$, $\max_i\{\hat{K}_i^{ab}(20)\} = \frac{1,000}{(2)(50)}(4) = 40$. Since $K^{ab}(20) > \max_i\{\hat{K}_i^{ab}(20)\}$, we conclude that alcohol establishments are attractive at a 20 ft distance. At 100 ft distance, we compute $K^{ab}(100) = \frac{1,000}{(2)(50)}(20) = 200$, $\min_i\{\hat{K}_i^{ab}(100)\} = \frac{1,000}{(2)(50)}(15) = 150$, $\max_i\{\hat{K}_i^{ab}(100)\} = \frac{1,000}{(2)(50)}(30) = 300$. Since $\min_i\{\hat{K}_i^{ab}(100)\} < K^{ab}(100) < \max_i\{\hat{K}_i^{ab}(100)\}$, we conclude that alcohol establishments do not present a significant influence at 100 ft distance.

Consider the Fig. 12 below, which illustrates this hypothetical relationship. Rather than the point estimates above, we can use this graph to evaluate distance ranges at which built environment exerts attractive or repellant influence. We can see below that alcohol establishments exert an attractive influence from 0 to 50 ft, as the observed cross-K values are greater than the range of simulated values. However, this influence becomes insignificant from 55 to 125 ft as the observed cross-K values lie within the simulated range.

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