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Is the recent surge in violence in American cities due to contagion?

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ABSTRACT

Firearm violence rates have increased in U.S. cities in 2020 and into 2021. We investigate contagious and non-contagious space-time clustering in shooting events in four U.S. cities (Chicago, Los Angeles, New York and Philadelphia) from 2016 to 2020. We estimate the dynamic reproduction number (*Rt*) of shootings, a measure of contagion, using a Hawkes point process. We also measure concentration over time using a spatial Gini index. We find that the contagious spread of violence increased in 2020 in several, but not all, of the cities we considered. In all four cities, non-contagious (Poisson) events comprised the majority of shootings across time (including 2020). We also find that the spatial location and concentration of shooting hot spots remained stable across all years. We discuss the implications of our findings and directions for future research.

1. Introduction

In the wake of a global pandemic and social unrest throughout the United States, firearm violence has risen to concerning levels across many of America's large urban cities. In their recent report of crime rates in the year 2020 across 34 cities, Rosenfeld and Lopez (2020) observed a 30% increase in homicide rates as compared to the previous year. Gun assaults increased 8% in this similar time period. Early media reports in 2021 suggest this troubling trend in lethal violence persists. Scholars currently seek explanations to this sharp rise in violence, while police departments and municipal governments are desperate to identify effective interventions to curb this growing epidemic. The causes and correlates of urban violence have proven difficult to parse apart.

Over the past decade, scholars have sought explanations of gun violence trends through spatiotemporal event modeling. In short, gun violence is believed to generate contagion effects, or repeat events. Put simply, firearm violence begets more firearm violence through several mechanisms. Concentrated social disadvantage in neighborhoods (Morenoff, Sampson, & Raudenbush, 2001; Papachristos, 2009; Tita & Ridgeway, 2007) as well as retaliatory events associated with gang violence and geographic turf wars (Brantingham, Tita, & Mohler, 2021; Green, Horel, & Papachristos, 2017; Papachristos, 2009; Papachristos, Braga, Piza, & Grossman, 2015; Rosenfeld, Bray, & Egley, 1999) aid this explanation of the spatial diffusion of gun violence. Firearm homicides, shots fired, and non-fatal shootings have been shown to demonstrate spatial spillover effects from one census tract to another (Cohen & Tita, 1999; Zeoli, Grady, Pizarro, & Melde, 2015; Zeoli, Pizarro, Grady, & Melde, 2014), while the spatial clustering of firearm violence has been observed to be non-random at both the county (Messner et al., 1999) and block levels (Ratcliffe & Rengert, 2008). Moreover, several studies have demonstrated that gun violence does indeed generate near-repeat spatiotemporal patterns (Caplan, Kennedy, & Piza, 2013; Haberman, Hatten, Carter, & Piza, 2021; Mazeika & Uriarte, 2019; Renda & Zhang, 2019; Sturup, Rostami, Gerell, & Sandholm, 2018; Wells, Wu, & Ye, 2012; Wu & Wells, 2016; Youstin, Nobles, Ward, & Cook, 2011). Such contagion effects may explain the spatial trends in firearm violence patterns, where some geographies within a city endure chronic and highly concentrated firearm violence while other areas of the same city experience significant fluctuations of these same events (Braga, Papachristos, & Hureau, 2010; Sadler, Melde, Zeoli, Wolfe, & O'Brien, 2021). Thus, contagious shooting events which spread to other geographies within a city may exacerbate overall levels of violence for a given city.

In this article we investigate the extent to which the rise in gun violence in 2020 (see Fig. 1) in four major U.S. cities can be explained by an increase in the contagiousness of shooting events. For this purpose we

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use a spatiotemporal Hawkes process (Loeffler & Flaxman, 2018; Mohler et al., 2021) to estimate the dynamic reproduction number (R_t) of shooting events, along with a non-contagious background Poisson rate of events that controls for day of week, month of year, and long-term trends that can generate stable space-time clustering patterns (Park, Schoenberg, Bertozzi, & Brantingham, 2021). The Hawkes process is a stochastic version of the susceptible-infected-removed (SIR) model in epidemiology (Rizoiu, Mishra, Kong, Carman, & Xie, 2018) and estimates events as a branching process where each event generates a probability of other events nearby in space and time. We also investigate space-time clustering and concentration of shooting events using a spatial Gini index applied to yearly data.

While public discourse has largely centered on the rise in homicide (Rosenfeld & Lopez, 2020) in 2020 and 2021, we focus on shootings for a couple of reasons. First, while homicide rates have increased across many urban communities, lethal violence remains a rare event when considered in space and time. Sparse data makes estimation of spatiotemporal patterns difficult to do with a level of certainty afforded through the use of shooting data, which are more frequent in number. Second, research has demonstrated a considerable overlap in space and time between homicide and non-fatal shootings (Braga et al., 2010), while event level analyses have demonstrated few differences in the demographic characteristics between those who live and those who die in shooting events. Rather what differentiates a non-fatal shooting from a fatal shooting are factors such as wound severity (Hipple & Magee, 2017), the caliber of weapon used (Braga & Cook, 2018), and the speed of emergency response. This body of work suggests the study of all shooting events can help to better understand spatiotemporal patterns in homicide.

The outline of the paper is as follows. In Section 2, we discuss related literature on crime contagion and gun violence. In Section 3, we discuss our methodology, including Hawkes process modeling and estimation, and a modified Gini index estimator used for measuring spatial concentration when event counts are low. In Section 4, we provide details on the open-source shooting data used for this study covering 2016–2020 from Chicago, Los Angeles, New York, and Philadelphia. In Section 5, we present the results of our analysis. We find that contagion is estimated to have increased in 2020 in several, but not all, cities. In all four cities, spontaneous non-contagious (Poisson) events are estimated to have comprised the majority of events across time, consistent with research on acoustic gunshot detection (Loeffler & Flaxman, 2018). We also found that the spatial location and concentration of shooting hotspots, as measured through the Gini index, remained stable across 2016–2020. In Section 6, we discuss the implications of our findings, limitations of our analysis, and directions for future research.

2. Related work on crime contagion and gun violence

The idea of crime contagion is not specific to the study of violent crime. Indeed, crime contagion is conceptually equivalent to ideas of event dependence and repeat victimization (Brantingham, Yuan, & Herz, 2020; Farrell & Pease, 1993; Johnson et al., 2007). The study of contagion is also not restricted to a single spatiotemporal scale. At the finest scale, the general model of contagion posits that there is some interaction between individual offenders and the physical and/or social environment that causally triggers subsequent events. In the case of property crimes, offenders 'learn something' about their targets (e.g., vulnerable houses) in the process of committing a first crime that attracts them back to that same location to repeat the prior success (Short, D'orsogna, Brantingham, & Tita, 2009). Alternatively, those same offenders might share what they learned with others who then act on that information (Wright & Decker, 1996). In the case of violent crime, an attack by one party on another triggers a retaliatory response (Brantingham et al., 2020; Decker, 1996; Randle & Bichler, 2017). Retaliation is driven either by a so-called 'code of the street' (Anderson, 1999), or by a deep-seated individual psychological need for revenge (Tedeschi & Felson, 1994). For both property and violent crime, the expected statistiscal pattern of crime contagion is that offspring events (the result of contagious spread) will occur near in time and space to the parental events (the triggers of contagious spread) (Mohler, Short, Brantingham, Schoenberg, & Tita, 2011).

With respect to gun violence, Fagan, Wilkinson, and Davies (2007) provided a useful model of the potential for social contagion that could help to explain the noted increases in homicide and gun violence in 2020. At the center of this model of social contagion of violence are firearms, and the influence these weapons have on social interactions. When guns are perceived as pervasive in a local context there are resultant changes in perceptions of danger associated with interpersonal disputes or conflicts between groups, creating an "ecology of danger." Given this backdrop, increases in the real or perceived threat of the use of weapons in disputes leads to the contagion of fear, whereby residents perceive not only that others have guns, but that they are likely to use them should the need arise. This leads to more people carrying a firearm both for self-protection in the event they are the target of a crime, and as a status symbol in order to dissuade others from attempting to victimize them. Finally, this process leads to the widespread adoption of violent identities, where people portend a tough or aggressive persona that denotes a willingness to engage in violence if challenged. Together, knowledge of increased rates of firearm violence in a local area can both set this process in motion, but also reinforces and amplifies the necessity of using guns to settle disputes.

In 2020, there were numerous events and social processes that may have helped to set the social contagion of violence processes in motion, and reinforce the necessity of carrying and using firearms to settle disputes. First, there were already signs of increased gun violence, including homicide, across U.S. cities starting in early 2020. Second, shortly after the COVID-19 pandemic hit the United States there was a surge in gun sales that was widely reported in the media (Levine &

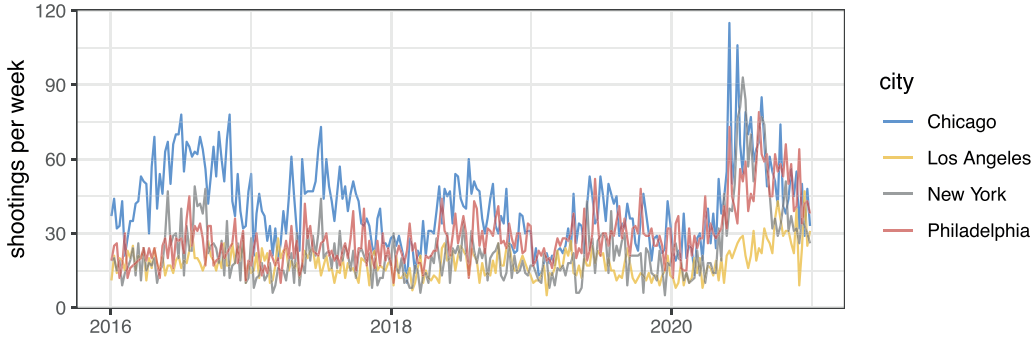

Fig. 1. Weekly number of shootings from 2016 to 2020 in Chicago, Los Angeles, New York, and Philadelphia.

McKnight, 2020). This was likely both a sign of increased anxiety about the potential consequences of the pandemic on personal safety, but also further stoked the fear of weapon-related violence. The murder of George Floyd at the hands of a Minneapolis police officer and the resultant social unrest targeted at the police more broadly may have further reinforced the need for people to engage in violent "self-help" when it came to interpersonal disputes, consistent with the work of Kirk and Papachristos on legal cynicism (Kirk & Papachristos, 2011).[1] The perceived inability of the police to protect residents from gun violence may have been reinforced by widespread discourse on the notion of de-policing across urban communities, whereby officers were unwilling to engage in proactive tactics to prevent or intervene in violence due, in part, to the backlash they faced in the wake of high profile officer involved shootings and the ongoing social distancing efforts associated with the pandemic. Together, this suggests that the message to communities was that gun crime was rising, people were arming themselves at record numbers, and the police were either unwilling or unable to intervene or investigate to prevent ongoing acts of violence.

Of course, it only does so much to hypothesize on all the various mechanisms at play here. Such a theoretical framework motivates the empirical question at hand: Is the recent increase in violence due to contagion? Answering this question is a necessary first step before research is extended to uncover the mechanisms that appear to explain the rise in gun violence, and whether theories that focus on contagious shootings play a critical role in the recent surge in gun violence.

3. Methodology

3.1. Branching process model of the dynamic reproduction number of shootings

We fit a Hawkes branching process (Bertozzi, Franco, Mohler, Short, & Sledge, 2020; Mohler et al., 2021) to shooting events with intensity,

$$\lambda(\mathbf{x},t) = \mu f(\mathbf{x}) h_d(t) h_m(t) h_y(t) + \sum_{t>t_i} R_{t_i} g_t(t-t_i;\omega) g_x(\mathbf{x}-\mathbf{x}_i;\sigma) \quad (1)$$

Here the background Poisson rate of events is assumed separable in space and time, where $f(\mathbf{x})$ models the spatial component of the background rate, fit using a Gaussian mixture model (GMM), and h_d, h_m, and h_y model day of the week, monthly, and yearly trends in the background rate. The second term in Eq. (1) models contagion between events, where R_t is the dynamic reproduction number (Bertozzi et al., 2020). Specifically, R_t is the expected number of secondary or offspring shooting events initiated by an event (under the branching process representation of the Hawkes process (Veen & Schoenberg, 2008)). The temporal component in the second term g_t is assumed to be exponential. The spatial component g_x is assumed to be Gaussian. The Hawkes branching process is related to the SIR model of infectious disease (Rizoiu et al., 2018), where the linear model in Eq. (1) estimates new cases in the absence of finite population effects. The model is fit to the data using an expectation-maximization algorithm as detailed in Liu, Carter, Ray, and Mohler (2021); Veen and Schoenberg (2008); Bertozzi et al. (2020).

To construct confidence intervals for parameters, we simulate multiple realizations of the Hawkes process fit to shooting data and then re-estimate model parameters to quantify uncertainty. The branching process representation of the Hawkes process is used for simulation, where first background Poisson events are generated from the Poisson process intensity $\mu f(\boldsymbol{x}) h_d(t) h_m(t) h_y(t)$. Offspring events are then iteratively added to the dataset, where each event generates $L \sim Pois(R_t)$ offspring events with spatial coordinates determined by adding random numbers drawn from g_x to the parent event location and a random number drawn from g_t to the time of the parent event. To better match the spatial distribution of events in the actual data, which lie on a street network, we re-sample the original dataset coordinates using the EM estimation branching probabilities to assign spatial locations to the background events in each simulation (as is done in Mohler et al. (2021)). Locations of simulated contagion events are then sampled from the continuous density $g_t(t-t_i;\omega)g_x(\mathbf{x}-\mathbf{x}_i;\sigma)$.

3.2. Spatial concentration of shootings

We also assess the yearly spatial concentration of shootings in each city by estimating the Gini index of aggregated event counts in 500 m × 500 m grid cells. We use a small-sample correction as outlined in Mohler, Brantingham, Carter, and Short (2019) by first fitting a Poisson-Gamma density to event counts and then estimating the Gini index as:

$$G = \frac{1}{N}\left(2\left(\frac{\sum_{i=1}^{N}(N+1-i)g_{(i)}}{\sum_{i=1}^{N} g_{(i)}}\right) - N - 1\right) \quad (2)$$

where g_i is drawn independently in grid cell i from the estimated Gamma distribution, N is the total number of cells, and $g_{(i)}$ are sorted counts.

4. Data sources

We use open-source shooting data from Chicago,[2] Los Angeles[3,4] New York,[5] and Philadephia.[6] The events contained a date and time of the event, along with the latitude and longitude of the location. Events without a location were removed from the analysis. Overall, the data consists of 10,715 events in Chicago, 4745 events in Los Angeles, 6037 events in New York, and 7489 events in Philadelphia across 2016–2020. Because the Hawkes process is a continuous model, exact repeat events (or events rounded to the nearest block) can cause the bandwidth of the spatial kernels to become small or approach zero during EM estimation. We therefore jitter the latitude and longitude locations with Gaussian noise with mean zero and standard deviation 10^{-3} degrees, equivalent to approximately 111 m.

5. Results

In Fig. 2 we display results of the goodness of fit of the Hawkes process model fit to data from Chicago, Los Angeles, New York, and Philadelphia. We present day of week, month of year, and yearly trends of the data compared to 100 realizations of the estimated Hawkes model. We also plot, in Fig. 3, the distribution of shootings from 2016 to 2020 and an example realization from the fitted Hawkes process. Overall, we find that the Hawkes process provides a plausible fit to the data in each city.

To further assess the goodness of fit, we apply residual analysis and thin the original shootings data by retaining events with probability,

$$p = \frac{\lambda_{inf}}{\lambda(x_i^s, t_i^s)}, \quad (3)$$

[1] Legal cynicism, in this instance, "refers to a cultural frame in which people perceive the law as illegitimate, unresponsive, and ill equipped to ensure public safety" (page 1190) (Kirk & Papachristos, 2011).

[2] https://data.cityofchicago.org/Public-Safety/Chicago-Shootings/fsku-dr7m

[3] https://data.lacity.org/Public-Safety/Crime-Data-from-2010-to-2019/63jg-8b9z

[4] https://data.lacity.org/Public-Safety/Crime-Data-from-2020-to-Present/2nrs-mtv8

[5] (https://data.cityofnewyork.us/Public-Safety/NYPD-Shooting-Incident-Data-Historic-/833y-fsy8

[6] https://www.opendataphilly.org/dataset/shooting-victims

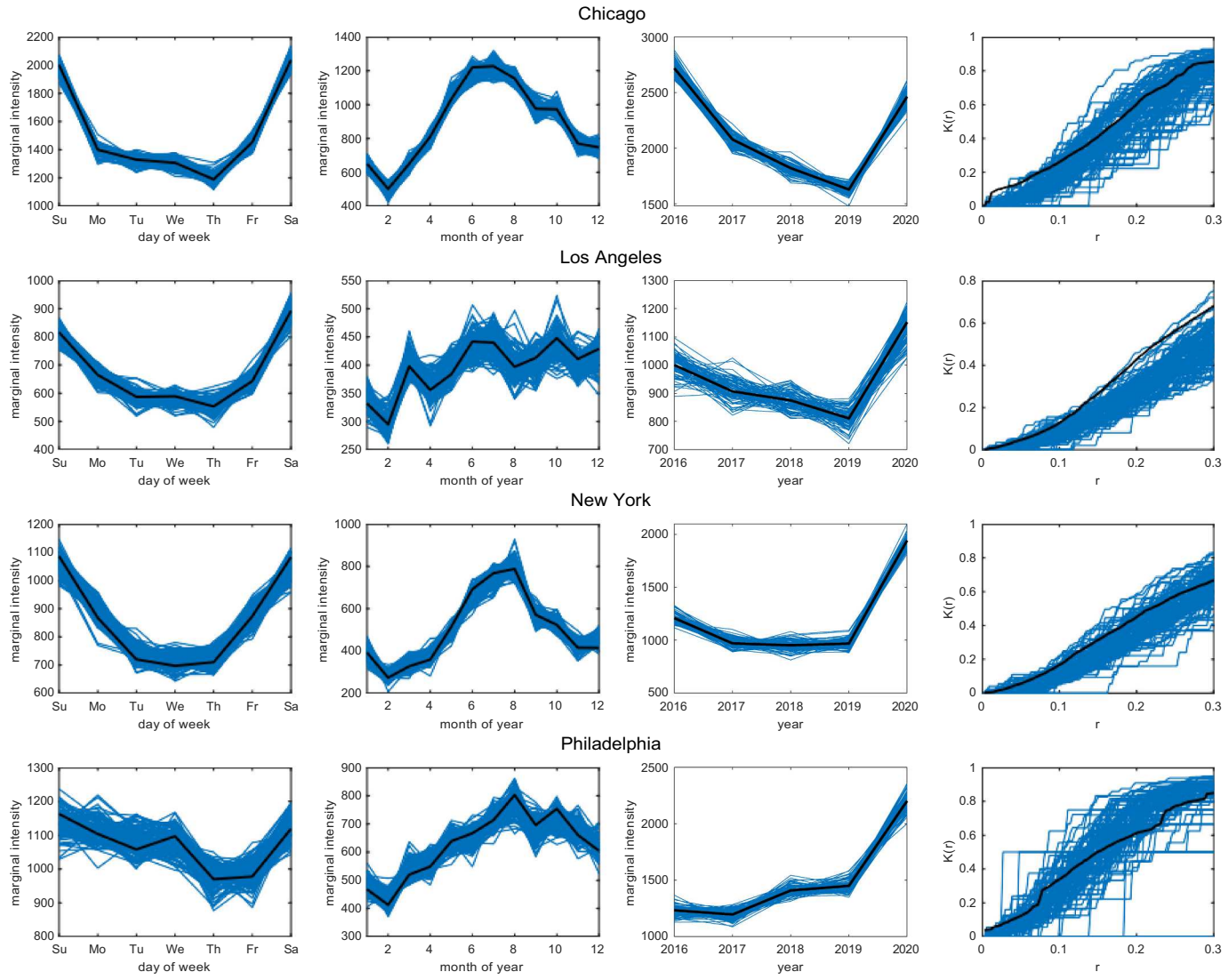

Fig. 2. Hawkes process goodness of fit to event shootings 2016–2020. From left to right, distribution of the number of events per day, per month, and per year in the observed data (black) and 100 fitted Hawkes process simulations (blue). Far left: K-function (black) of fitted Hawkes process thinned residuals of the shootings data (thinned with probability $\lambda_{inf}/\lambda(t_i)$). K-function for 100 realizations of a constant rate Poisson process (blue). Radius r measured in degrees. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where λ_{inf} is the infimum of the intensity on the domain of each city. When the model is correctly specified, the thinned residual points are a realization of a constant-rate Poisson process (Schoenberg, 2003), whereas there will be an excess or deficit of events in regions the estimated intensity under- or over-estimates the true intensity. We can then compare the distribution of the thinned events to that of a unit rate Poisson process to assess the goodness of fit of the intensity. One way to make this comparison is using Ripley's K function (Ripley, 1976), the average number of events $K(r)$ within a radius r of each event. In Fig. 2 we display the average K-function for the thinned residuals (averaged over 100 thinned residual realizations) along with the K-function of 100 simulated Poisson processes. In Fig. 2, we find that the average K-function of the thinned residuals of the data is plausibly Poisson (with the exception of small scales in Chicago, where some excess clustering is not explained by the model).

In Fig. 4 we display the estimated time-varying reproductive number (R_t) of shootings along with 95% confidence intervals. While Philadelphia and Los Angeles have higher estimated reproduction numbers in 2020 compared to 2019 (significant at the 0.009 and 0.02 level respectively using a two-sided t-test), the reproduction number in New York is estimated to have gone down in 2020 and the differences in Chicago's reproduction number over time are not statistically significant. In general, Philadelphia and New York have higher estimated reproduction numbers than Chicago and Los Angeles. This could be due to geographical differences between cities, such as the size of street networks. To the extent contagion effects are less localized in Chicago and Los Angeles, our methodology, which focuses on distance, is not well suited to detect non-local effects.

One by-product of the EM estimation algorithm is that a probabilistic branching structure is estimated alongside model parameters. We therefore have an estimate of the number of events that are spontaneous (generated by the background Poisson rate) vs. the number of events that can be attributed to contagion. In Table 1, we show the estimated number of contagious vs. spontaneous non-contagious generated events for each city and each year. Here we find that a majority of events are estimated to be spontaneous, across cities and years, consistent with recent Hawkes process estimation of acoustic gun- shot detection events (Loeffler & Flaxman, 2018). At the same time, we find higher levels of contagion in the present study than in acoustic gunshot detection events and considerable variation across cities in the level of contagion, from the highest average of 30% in New York City to the lowest of 15% in Chicago.

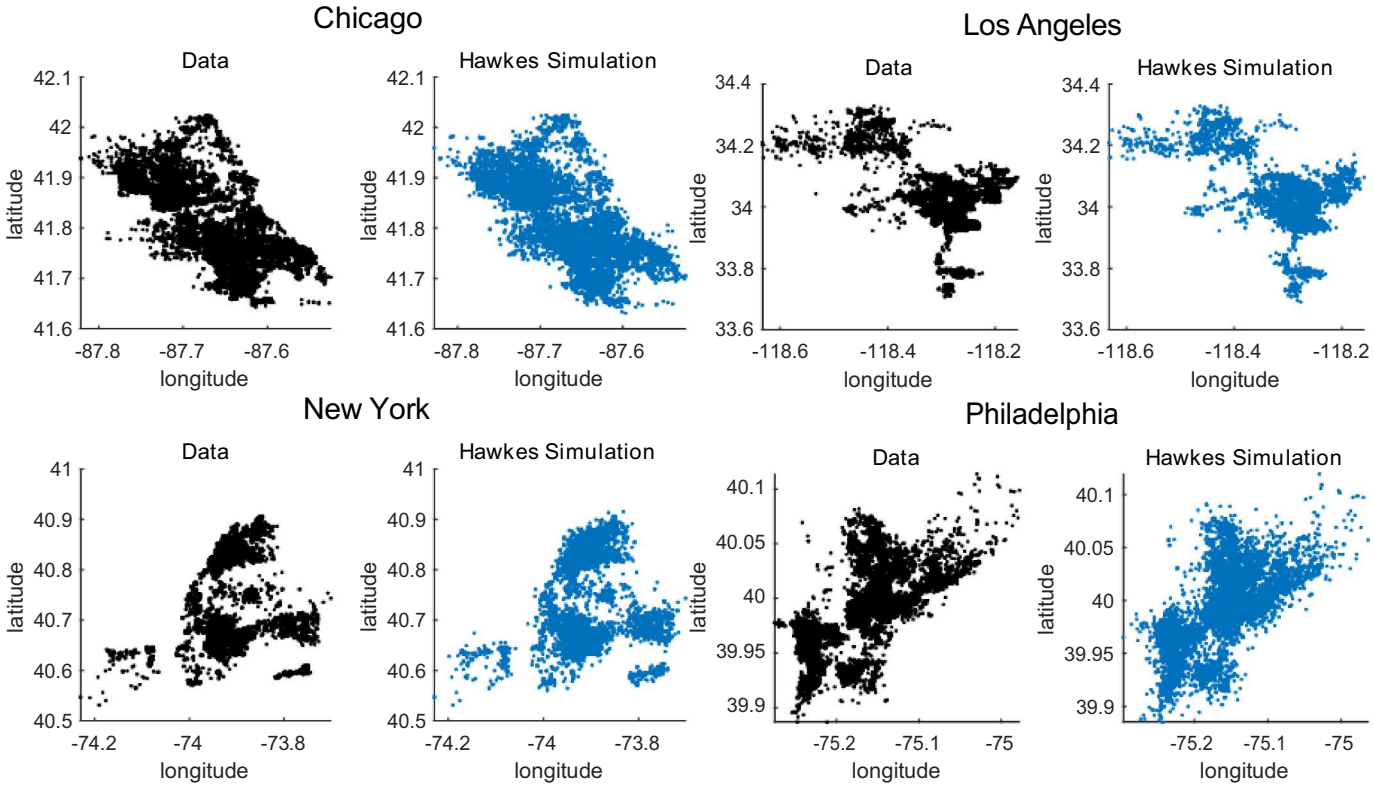

Fig. 3. Scatter plot of shooting event lat/long coordinates from the 2016–2020 data (black) and scatter plot of event coordinates of one realization of a simulated Hawkes process (blue) fit to shootings data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

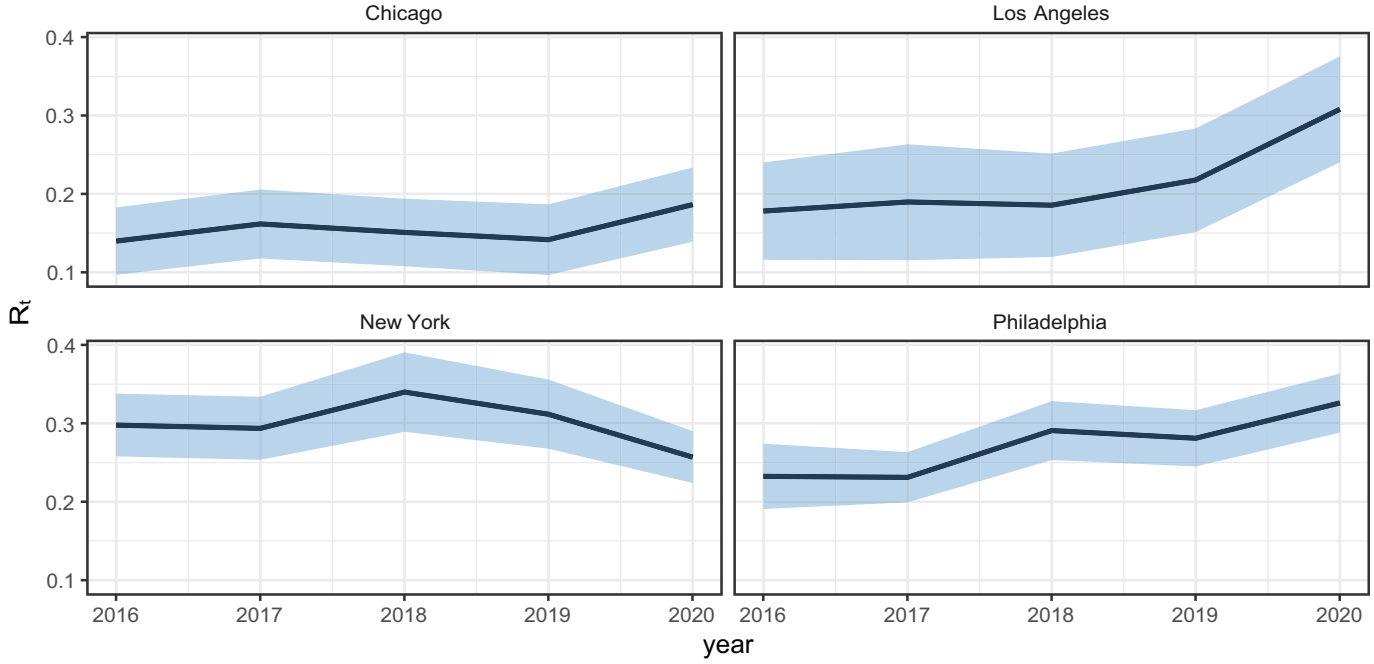

Fig. 4. Estimated dynamic reproduction number, *Rt*, of shootings for each year along with 95% confidence interval.

In Fig. 5 we display yearly estimates of the Gini index and in Fig. 6 we display spatial locations of shooting hotspots that contain 25% and 50% of events (the 25% and 50% percentages are selected using the convention established by Weisburd (2015). Here we find that the concentration of shootings is high across cities and years, where the Gini index is in the range of 0.65 to 0.85. For reference, the Gini index ranges from 0 (spatially uniform) to 1 (complete concentration in a single grid cell). We also find that concentration is consistent across years and that hotspots appear, for the most part, in the same locations from year-to-year in each city. In Table 2, we display the percentage of hotspots

Table 1
Estimated number of spontaneous (Sp.) events vs. the number and percent- age of contagion (Cnt.) events.

	Chicago			Los Angeles			New York			Philadelphia		
Year	Sp.	Cnt.	%	Sp.	Cnt.	%	Sp.	Cnt.	%	Sp.	Cnt.	%
2016	2349	370	14%	829	171	17%	851	357	30%	947	286	23%
2017	1740	330	16%	734	167	19%	682	284	29%	919	276	23%
2018	1547	271	15%	714	156	18%	628	323	34%	1000	409	29%
2019	1402	226	14%	634	170	21%	666	301	31%	1044	406	28%
2020	2000	458	19%	791	355	31%	1443	499	26%	1483	718	33%

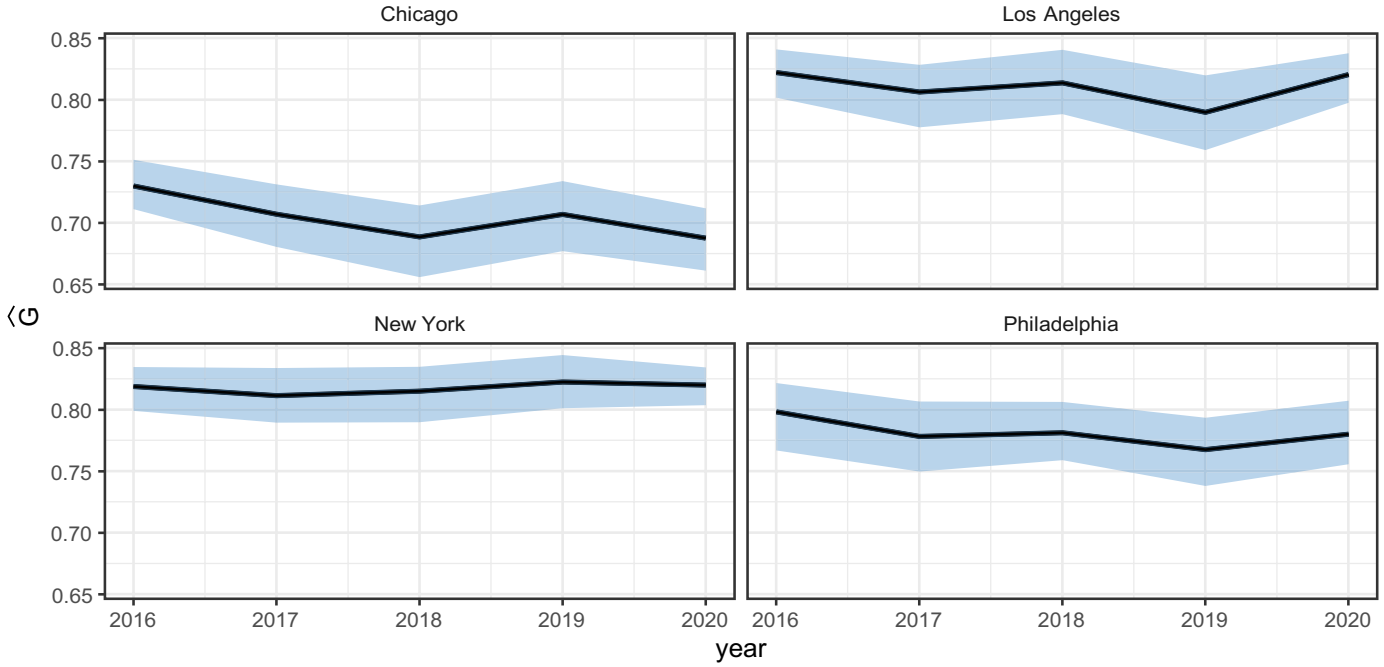

Fig. 5. Estimated yearly Gini index, $\hat{G}$, of shootings using a grid of 500 m × 500 m cells. 95% confidence interval shown in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

that are the same from one year to the next containing 50% of shootings. For example, between 2019 and 2020, 62.5% of hotspots were the same in Los Angeles, 66.7% were the same in Chicago, and 58.5% and 86.7% overlapped in New York and Philadelphia respectively.

6. Discussion

Understanding the potential causes underlying a recent surge in gun violence in urban American cities is necessary for designing effective interventions. Here we find that the contagious spread of violence—-where prior shootings trigger future gun violence—has played a mixed roll in the surge.

The four cities examined here all display some measure of contagious spread of gun violence, but contagious events are the minority of shootings. Overall in 2020, contagious events made up between 19% (Chicago) and 33% (Philadelphia) of all shootings. The remainder should be considered spontaneous or non-contagious events tied to structural features of the environment. Surprisingly, the relative volume of contagious violence moved in different directions depending upon the city in question. Contagious shootings made up a greater share of such violence in Los Angeles and Philadelphia in 2020 compared with 2019 (increasing from 21% to 31% and 28% to 33% of events, respectively), remained statistically unchanged in Chicago (increasing non-significantly from 14% to 19% of events), and actually went down in New York City (decreasing from 31% to 26% of events).

The bigger shift (by volume) in shootings is tied to structural features of the environment and an overall increase in the background temporal intensity of events. This is reflected in the high percentage of spontaneous events in Table 1 and the high and temporally stable Gini index of spatial concentration in Fig. 5. Non-contagious or spontaneous events made up between 67% (Philadelphia) and 81% (Chicago) of all shootings in 2020. With respect to time, across all four cities there was an abrupt shift to much higher baseline shooting intensity between 2019 and 2020 (see Fig. 2). In Chicago, the shift was to a baseline intensity last exceeded in 2016. In the remaining cities, the shift was to a baseline intensity higher than anything seen in the last five years.

It has long-been recognized that crime is unevenly distributed across space forming areas of high and low concentration (Mohler et al., 2019; Weisburd, 2015). Indeed, crime hotspots are recognized at all geographic scales of resolution (Brantingham, Dyreson, & Brantingham, 1976). The relative stability of geographic crime patterns has received less attention overall, though this remains an important issue for designing crime prevention strategies. In Mohler, Short, & Brantingham (2017) it is suggested, for example, that there is a tradeoff between the concentration of crime in space (Weisburd, 2015) and the stability of the associated hotspots. In general, at fine spatiotemporal scales crime is much more concentrated, but hotspots also frequently shift from place to place (see also Wang, Zhang, Bertozzi, and Short, 2021). At coarse spatio-temporal scales, crime is more diffuse, but the resulting hotspots also rarely move around. Braga et al. (2010) examined the spatial stability of gun violence in Boston from 1980 to 2008. Their results "... suggest that gun violence upswings and downturns are largely concentrated at a small number of gun violence hot spots that intensify and diminish over time". It is possible that gun violence trends at these

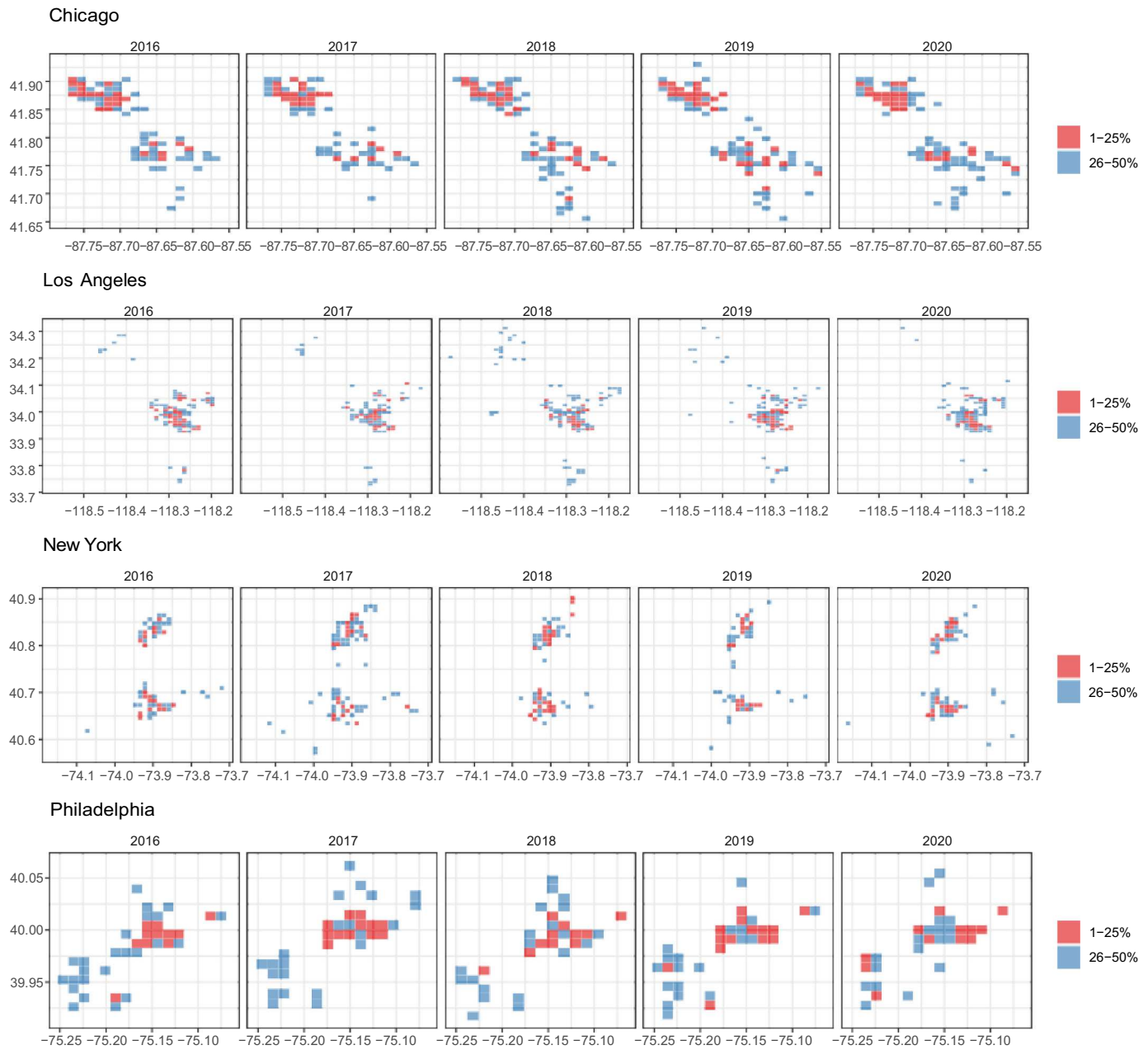

Fig. 6. Hotspots (1 km × 1 km) each year accounting for 25% of shooting events (red) and 50% of shooting events (blue and red combined). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Stability of hotspots over time. Percent overlap of hotspots from year to year containing 50% of shootings

Year	Los Angeles	Chicago	New York	Philadelphia
2016–2017	71.59%	74.19%	49.40%	67.65%
2017–2018	57.02%	63.01%	59.02%	80.65%
2018–2019	57.00%	70.27%	57.69%	69.70%
2019–2020	62.50%	66.67%	58.46%	86.67%

places follow trajectories that are consistent with a spatial diffusion process" (p. 50). Moreover, they conclude that less than 3% of micro places in Boston had volatile levels of gun violence.

The policy implications of our findings are two-fold. First, increases in the proportion of contagious gun violence may be tackled through short-term, spatially-focused efforts to disrupt contagious spread. In the case of gang-related violence, this might be achieved through community-led violence interruption efforts (Park et al., 2021), or traditional crime suppression (Rosenfeld, Deckard, & Blackburn, 2014). Second, the jump in non- contagious spontaneous events are likely to require efforts to achieve larger-scale, structural changes in the environment and routine behaviors, such as remediating vacant lots and abandoned housing (MacDonald, Branas, & Stokes, 2019). To the extent that the surge in 2020 was tied to routine activities (Cohen & Felson, 2003) unique to the pandemic, a return to "normal life" might help cities naturally reverse course. If structural changes underlying the surge have become more embedded, then it may take a considerable period of time to return to the conditions that prevailed before 2020. In Chicago, for example, it took approximately three years to see a decrease in baseline crime intensity after the 2016 spike in shootings, which was of a similar magnitude to the recent increase. All things being equal, we might expect a return to 2019 levels to take at least as long without any specific

strategies to improve local conditions.

This study is not without limitations. First, while research suggests the study of fatal and nonfatal shootings is useful for understanding urban violence, public discourse centered on urban violence has largely focused on the increase in homicides across numerous U.S. jurisdictions across 2020 and 2021. Because of the rarity of homicide events in space and time, the analyses presented in the current study were not well suited for a strict focus on homicide. Second, research suggests a possibility that contagious violence may spread through social networks that are non-local, whereby shooting events in one part of the city may motivate shootings in distant areas. Our focus on spatiotemporal patterns in gun violence would not capture such events.

A further limitation of our analysis is that we did not explicitly account for changes in the intensity of shootings due to exogenous shocks, such as pandemic related lock-downs or protests. Crime contagion can be facilitated by multiple distinct processes and may be connected simultaneously to unique features of individual routine activities, social networks and community social norms (e.g. about retaliation). As a result, endogenous or exogenous changes in any of these domains may also have an indirect impact on crime contagiousness. For example, the wide-spread 'lock down' and social distancing practices adopted in response to the global pandemic in 2020–2021 are known to impact social dynamics in general (e.g., urban mobility). It is reasonable to expect that these changes impacted crime contagiousness. Current evidence suggests that the impact of COVID-19 'stay-at-home' orders on crime volume was generally more muted than expected (Mohler et al., 2020; Piquero et al., 2020). It also appears that criminal street gangs also did not immediately take advantage of the pandemic to expand their activity (Brantingham et al., 2021). If the pandemic is a primary underlying cause of the increase in violence contagiousness, observed in three of the four cities in 2020, then we can hope that a return to more normal social conditions may lead to a return to more 'normal' patterns of violence.

However, in at least two of these cities (Los Angeles, Philadelphia) the increases in crime contagiousness in 2020 appear to be part of a trend stretching back to at least 2018. In New York, the decrease in crime contagiousness also appears to be part of a pattern of decline (or reversion to the mean) after a peak in 2018. These patterns would seem to implicate changes in social dynamics that predate the pandemic that are not necessarily the same across settings. Future research will be required to tease apart what was happening on the ground. Among many possible avenues of investigation, we believe it is worth assessing the role of changes in the size and organization of gangs, the availability of guns and higher caliber ammunition (Braga & Cook, 2018), the perceived legitimacy of the police and government (Kirk & Papachristos, 2011; LaFree, 2018), and the continued infiltration of social media into daily life.

Authors statement

Authors listed in alphabetical order. All authors contributed equally to the design of the research and writing of the paper. G.M. performed the data analysis.

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