IS GUN VIOLENCE CONTAGIOUS?

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ORIGINAL PAPER

Is Gun Violence Contagious? A Spatiotemporal Test

Charles Loeffler[1] · **Seth Flaxman**[2]

Abstract
Objectives Existing theories of gun violence predict stable spatial concentrations and contagious diffusion of gun violence into surrounding areas. Recent empirical studies have reported confirmatory evidence of such spatiotemporal diffusion of gun violence. However, existing space/time interaction tests cannot readily distinguish spatiotemporal clustering from spatiotemporal diffusion. This leaves as an open question whether gun violence actually is contagious or merely clusters in space and time. Compounding this problem, gun violence is subject to considerable measurement error with many nonfatal shootings going unreported to police.
Methods Using point process data from an acoustical gunshot locator system and a combination of Bayesian spatiotemporal point process modeling and classical space/time interaction tests, this paper distinguishes between clustered but non-diffusing gun violence and clustered gun violence resulting from diffusion.
Results This paper demonstrates that contemporary urban gun violence in a metropolitan city does diffuse in space and time, but only slightly.
Conclusions These results suggest that a disease model for the spread of gun violence in space and time may not be a good fit for most of the geographically stable and temporally stochastic process observed. And that existing space/time tests may not be adequate tests for spatiotemporal gun violence diffusion models.

Keywords Gun violence · Contagion · Spatiotemporal methods

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SCALABLE HIGH-RESOLUTION FORECASTING OF SPARSE SPATIOTEMPORAL EVENTS WITH KERNEL METHODS: A WINNING SOLUTION TO THE NIJ "REAL-TIME CRIME FORECASTING CHALLENGE"

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Department of Mathematics and Data Science Institute, Imperial College London[†]*, Grab, Singapore*[‡]*, Amazon, Inc.*[§] *and Department of Criminology, University of Pennsylvania*[¶]

We propose a generic spatiotemporal event forecasting method, which we developed for the National Institute of Justice's (NIJ) Real-Time Crime Forecasting Challenge (NIJ, 2017). Our method is a spatiotemporal forecasting model combining scalable randomized Reproducing Kernel Hilbert Space (RKHS) methods for approximating Gaussian processes with autoregressive smoothing kernels in a regularized supervised learning framework. While the smoothing kernels capture the two main approaches in current use in the field of crime forecasting, kernel density estimation (KDE) and self-exciting point process (SEPP) models, the RKHS component of the model can be understood as an approximation to the popular log-Gaussian Cox Process model. For inference, we discretize the spatiotemporal point pattern and learn a log intensity function using the Poisson likelihood and highly efficient gradient-based optimization methods. Model hyperparameters including quality of RKHS approximation, spatial and temporal kernel lengthscales, number of autoregressive lags, bandwidths for smoothing kernels, as well as cell shape, size, and rotation, were learned using crossvalidation. Resulting predictions significantly exceeded baseline KDE estimates and SEPP models for sparse events.

1. Introduction. Spatiotemporal forecasting of crime has been the focus of considerable attention in recent years as academic researchers, police departments, and commercial entities have all sought to build forecasting tools to predict when and where crimes are likely to occur (Perry et al., 2013). The earliest crime forecasting tools consisted of nothing more than pin-maps (See, for example, Figure 1). Prior week's crimes were mapped and qualitative assessments of density, location, stability and significance were

[*]Support was provided by the EPSRC (EP/K009362/1). Source code to reproduce our results is available: https://github.com/MichaelChirico/portland.

Keywords and phrases: spatial statistics, time series, supervised learning, spatiotemporal forecasting, Cox process, RKHS

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Background

- Empirical observations:
  - ~ 10K fatal homicidal shootings per year in U.S.
  - ~ 50K non-fatal shootings per year in U.S.
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  - **Are shootings really contagious or just non-randomly clustered?**

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- **Contribution:**
  - **Using a Hawkes process Model and AGLS data to separate endemic from epidemic clustering**

Existing Tests for Violence Contagion

- Using Knox test, Ratcliffe and Rengert (2012) report clustering of firearm assaults at <2 weeks and <400 ft
  - How do we know that this clustering is reactive rather than stable and stochastic?
  - How do we overcome low count aggregation problems?

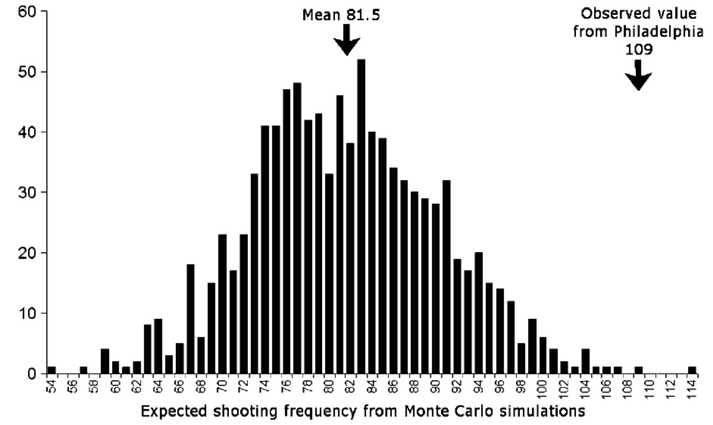
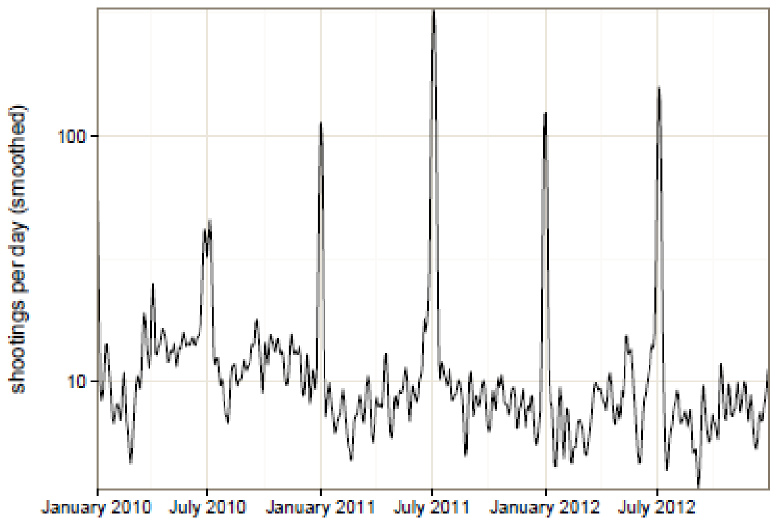


Figure 3. Monte Carlo simulation results from 999 runs examining the expected frequency of shootings in the range 0–14 days, and less than 400 feet from a previous shooting.

Source: Ratcliffe and Rengert (2012)

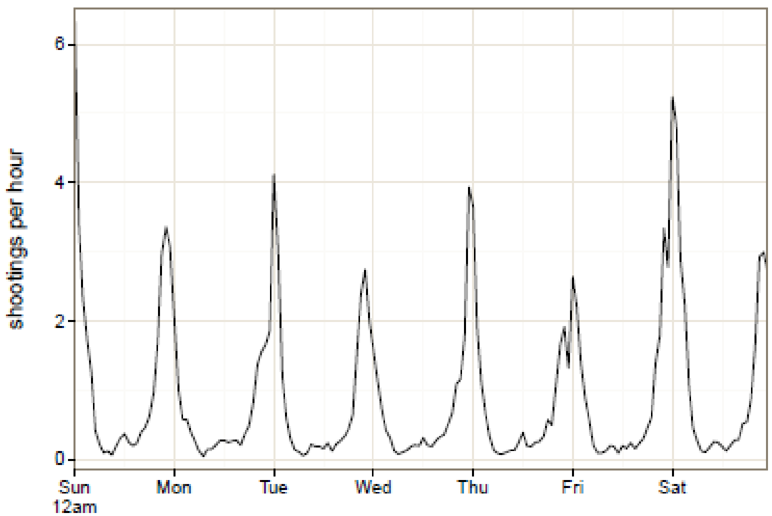
Gun Violence in Washington, D.C. 2010-2012



(a) Time series

- **Highly clustered in time (macro-scale)**

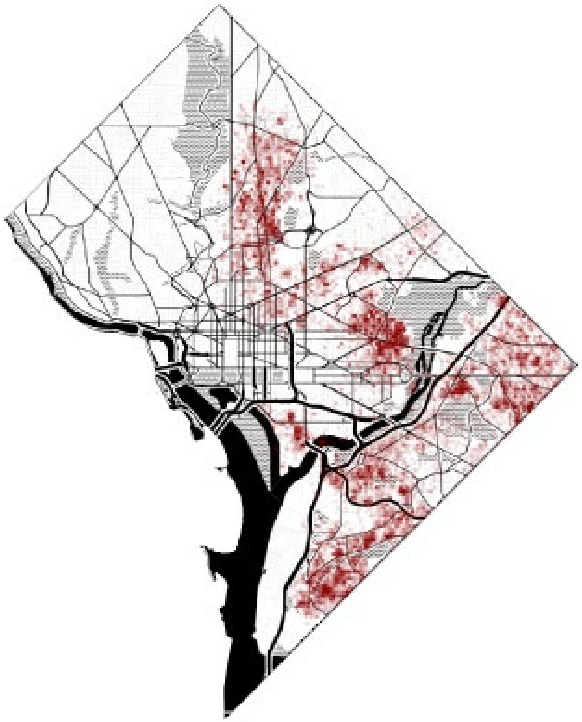
Gun Violence in Washington, D.C. 2010-2012



(b) Hour of week trends

- Highly clustered in time (macro-scale)
- **Highly clustered in time (micro-scale)**

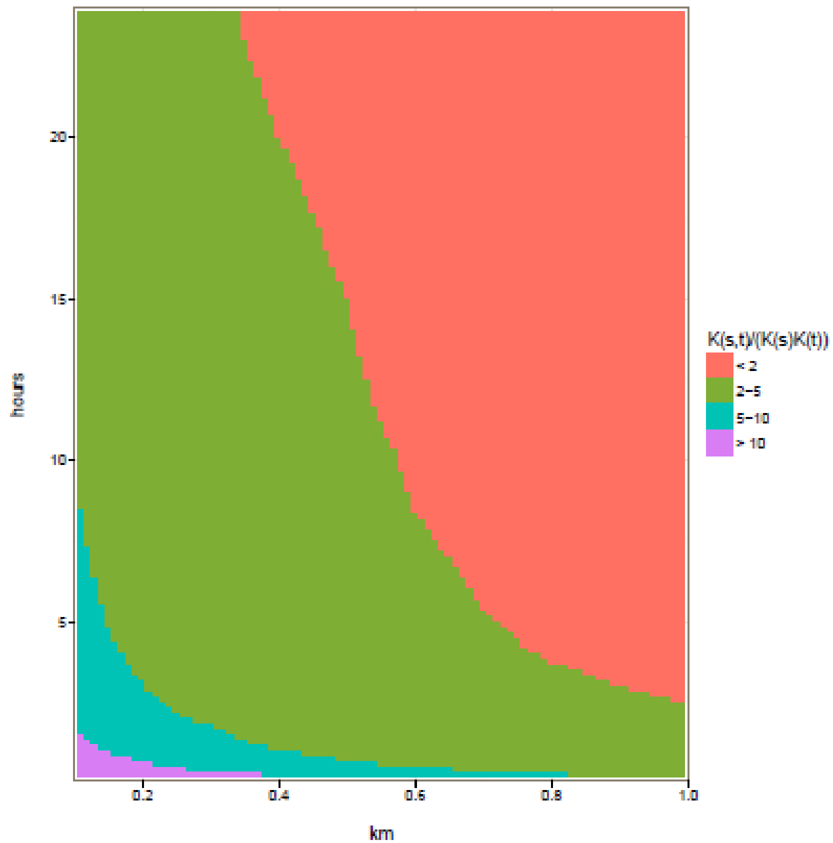
Gun Violence in Washington, D.C. 2010-2012



(c) AGLS

- Highly clustered in time (macro-scale)
- Highly clustered in time (micro-scale)
- **Highly clustered in space**

Gun Violence in Washington, D.C. 2010-2012



(d) Ripley's K-Function

- Highly clustered in time (macro-scale)
- Highly clustered in time (micro-scale)
- Highly clustered in space
- **Highly clustered in space-time**

Gun Violence in Washington, D.C. 2010-2012

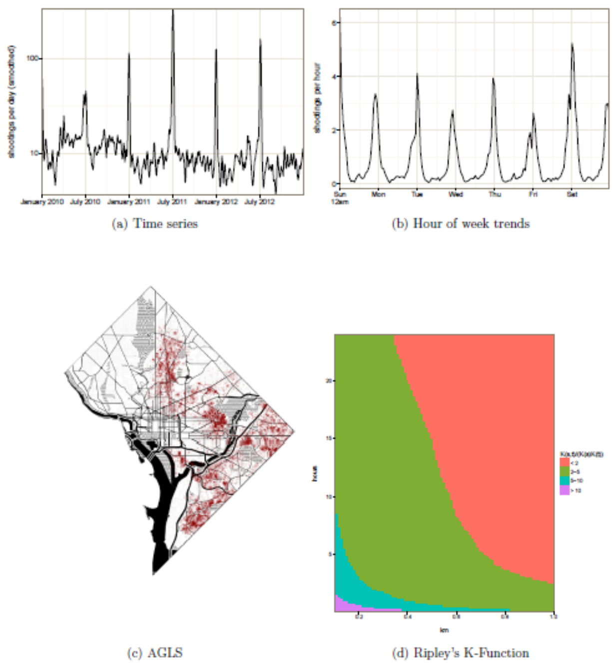
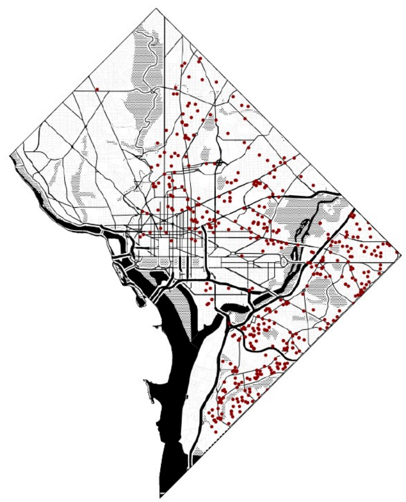


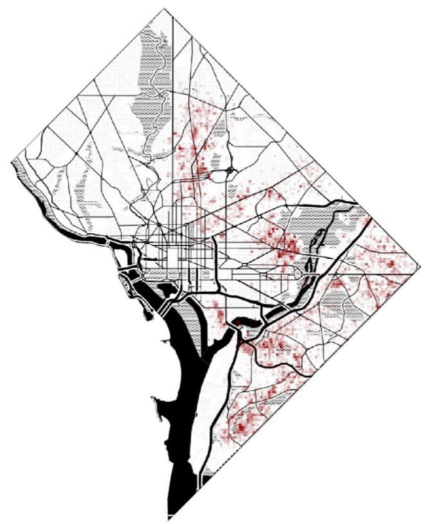
Figure 1: (a-b). Temporal distribution of acoustically located gunshots in Washington D.C., 2011-2012. (c). Spatial distribution of AGLS, 2010-12. (d). Ripley's K-Function.

- **A null hypothesis of CSR/CSTR is implausible**
- **But what does a scalable infectious spatiotemporal point process model look like and can it be estimated with conventional violence data?**

Spatial and Temporal Distributions of Firearm Assaults and Shots Fired in Washington, D.C., 2011

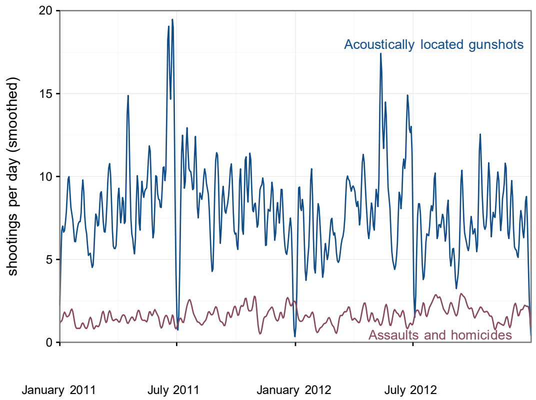


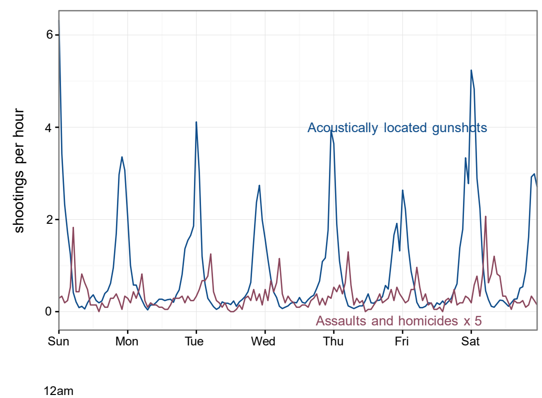
Firearm Assaults



AGLS

Photo by U.S. Army RDECOM





Methods

- **Hawkes Process Model**

$$\lambda(x,y,t) = m_0 \cdot \mu(x,y,t) + \theta \sum_{i:t_i<t} \omega \exp\left(-\omega(t-t_i)\right) \frac{1}{2\pi\sigma^2} \exp\left(-((x-x_i)^2 + (y-y_i)^2)/(2\sigma^2)\right)$$

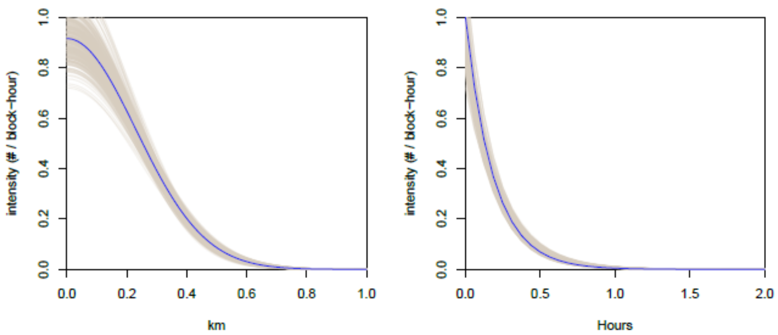
  - **Background Intensity**
    - **Kernel Density Estimation**
      - **Gaussian Spatial Kernel**
      - **Separable components**

$$\hat{\mu}(s,t) = m_0 \cdot \hat{\mu}(s)\hat{\mu}(t)$$

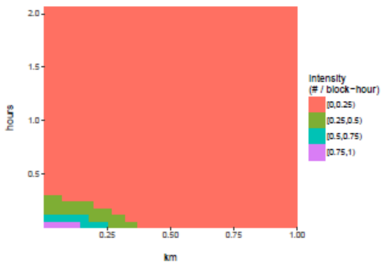
  - **Conditional Intensity**
    - $\mathcal{L}(t_1,\ldots,t_n|\theta,\omega,\mu) = \prod_i \lambda(t_i)\exp(-\int_{t=0}^{T} \lambda(t)dt)$
  - **Ratio of intensities provides fraction of events attributed to each intensity**
    - **For event i at location (x_i, y_i, t_i)**

$$r_i = m_0 \cdot \mu(x_i, y_i, t_i)/\lambda(x_i, y_i, t_i)$$

Results



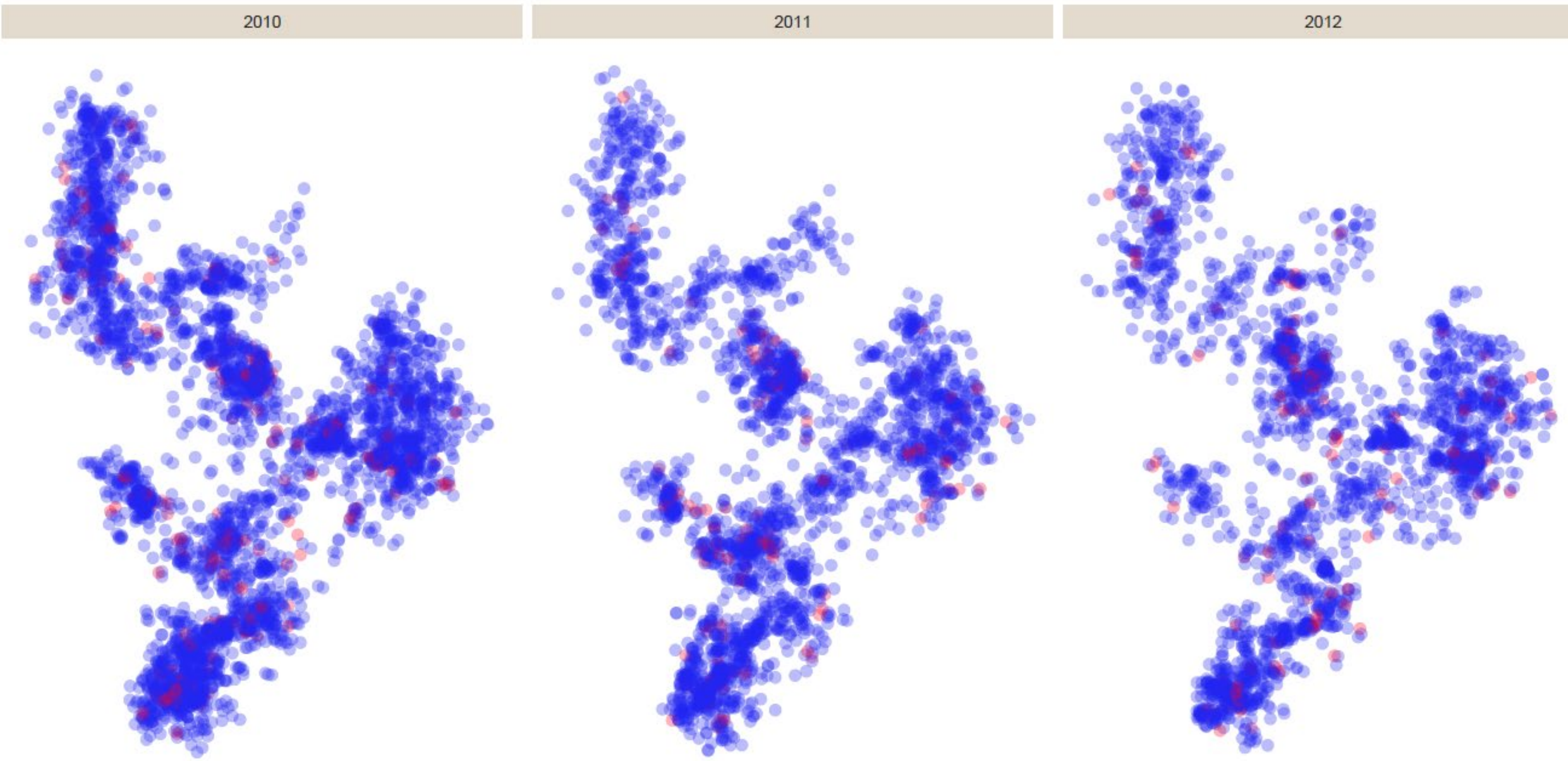
(a) Spatial conditional intensity (b) Temporal conditional intensity



(c) Spatiotemporal conditional intensity

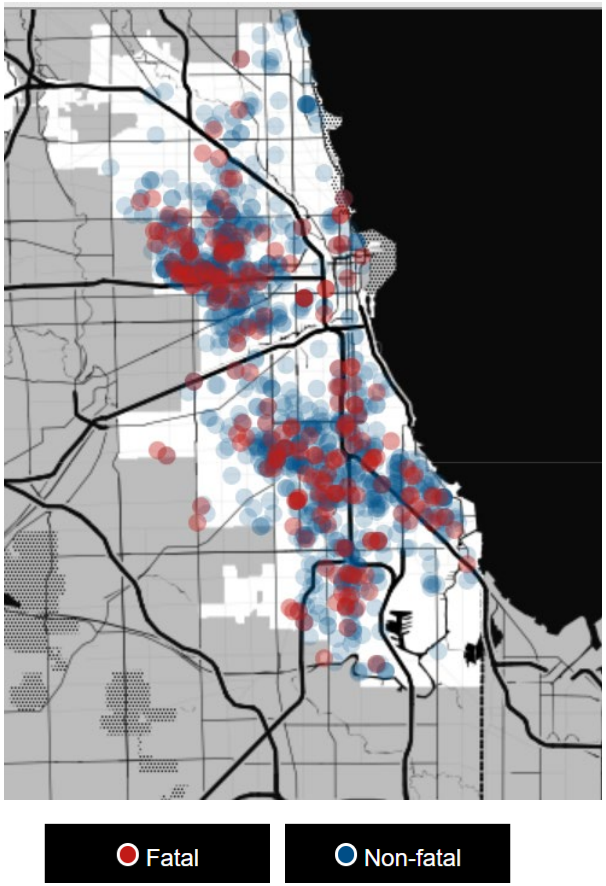
- 0.89 endogenous intensity
- 0.11 conditional intensity
- Note: very similar to motive split of fatal shootings (.84/.16)
- Temporal lengthscale is 12 mins
- Spatial lengthscale is 230 meters
- Note: more consistent with reactive behavior than extended retaliation

Classified Gunshot Events



Background (blue) versus “triggered” (red) shootings, by year.

Chicago Preliminary Results (2016-2018



Source: Chicago Tribune (2019)

- 0.24 endogenous intensity
- 0.76 conditional intensity
- Note: pretty similar to motive split of fatal shootings (.34/.66)
- Temporal lengthscale is 72 days
- Spatial lengthscale is 0.32 km
- Note: more consistent with extended retaliation

Implications and Next Steps

- Gun violence is highly clustered in space and time
  - Null hypothesis of CSR/CSTR randomness will always be rejected
- Using a space-time interaction test with space-time heterogeneity
  - In DC, most clustering is well-described by an endemic process
  - A small fraction is consistent with a Hawkes-type diffusion process
  - Triggered events occur within a narrow space-time radius
- Replication in cities with different gang structures
  - In Chicago, most violence is consistent with diffusion.
  - Trigger events occur over larger distances and greater times
- Replication with different types of violence--

SCIENCE

Mass Killings May Have Created Contagion, Feeding on Itself

By BENEDICT CAREY JULY 26, 2016

London tries to treat knife crime surge as public health epidemic

AFP Antoine POLLEZ, AFP · December 21, 2018

- Other approaches to estimating underlying intensity

Questions?

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References

1. C. Loftin, *Bulletin of the New York Academy of Medicine* 62, 550 (1986).
2. National Research Council (U. S.). *Understanding and preventing violence* (National Academy Press, Washington, DC, 1993).
3. J. Fagan et al., *The Cambridge Handbook of Violent Behavior and Aggression*, (Cambridge University Press, New York, 2007), pp. 688–726.
4. NRC, Contagion of Violence - Workshop Summary, *Tech. rep.*, Institute of Medicine and National Research Council of the National Academies, Washington, D.C. (2012).
5. W. Skogan, S. Hartnett, N. Bump, J. Dubois, Evaluation of CeaseFire-Chicago, *Tech. rep.*, U.S. Department of Justice, Washington, D.C. (2009).
6. D. W. Webster et al., *Journal of Urban Health* 90, 27 (2012).
7. S. D. Johnson, *Journal of Experimental Criminology* 4, 215 (2008).
8. G. O. Mohler et al., *Journal of the American Statistical Association* 106, 100 (2011).
9. M. Short et al., *Proceedings of the National Academy of Sciences* 107, 3961 (2010).
10. M. Townsley et al., *British Journal of Criminology* 43, 615 (2003).
11. J. Cohen, G. Tita, *Journal of Quantitative Criminology* 15, 451 (1999).
12. J. D. Morenoff, R. J. Sampson, S. W. Raudenbush, *Criminology* 39, 517 (2001).
13. G. Tita, J. Cohen, *Spatially Integrated Social Science* (Oxford University Press, New York, 2004), pp. 171–204.
14. J. H. Ratcliffe, G. F. Rengert, *Security Journal* 21, 58 (2008).
15. A. Braga, A. Papachristos, D. Hureau, *Journal of Quantitative Criminology* 26, 33 (2010).
16. R. Rosenfeld, T. Bray, A. Egley, *Journal of Quantitative Criminology* 15, 495 (1999).
17. S. F. Messner, *et al.*, *Journal of Quantitative Criminology* 15, 423 (1999).
18. G. Tita, G. Ridgeway, *Journal of Research in Crime and Delinquency* 44, 208 (2007).
19. A. Papachristos, *American Journal of Sociology* 115, 74 (2009).
20. G. d. Tarde, *The Laws of Imitation* (H. Holt, 1903).
21. J. Coleman, E. Katz, H. Menzel, *Sociometry* 20, 253 (1957).
22. N. A. Christakis, J. H. Fowler, *New England Journal of Medicine* 357, 370 (2007).
23. M. Short, G. Mohler, P. J. Brantingham, G. Tita, *Discrete and Continuous Dynamical Systems* 19, 1459 (2014).
24. MPD, A Report on Juvenile and Adult Homicide in the Distict of Columbia, *Tech. rep.*, Metropolitan Police Department Washington, D.C. (2006).