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ORIGINAL PAPER

Is Gang Violent Crime More Contagious than Non-Gang Violent Crime?

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Abstract

Objectives Gangs are thought to enhance participation in violence. It is expected then that gang-related violent crimes trigger additional crimes in a contagious manner, above and beyond what is typical for non-gang violent crime.

Methods This paper uses a multivariate self-exciting point process model to estimate the extent of contagious spread of violent crime for both gang-related and non-gang aggravated assaults and homicides in recent data from Los Angeles. The degree of contagious cross-triggering between gang-related and non-gang violent crime is also estimated.

Results Gang-related violence triggers twice as many offspring events as non-gang violence and there is little or no cross-triggering. Gang-related offspring events are significantly more lethal than non-gang offspring events, but no more lethal than non-contagious background gang crimes.

Conclusions Contagious spread of gang-related violent crime is different from contagion in non-gang violence. The results support crime prevention policies that target the disruption of gang retaliations.

Keywords Homicide · Assault · Gangs · Point process · Violence prevention

Introduction

The historically low violent crime rates in large- and mid-sized cities today mask the significant challenges posed by criminal street gangs. For example, while the total numbers of homicides per year in Chicago and Los Angeles are significantly below where they were even 10 years ago, the fraction of homicides that are gang-related has remained consistently high (Hutson et al. 1995; Egley and McDaniel 2012; Valasik et al. 2017). That gang

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crime tends to be more violent than non-gang crime has long been recognized (see Pyrooz et al. 2016). Gang violent crime also tends to be much more lethal than non-gang violent crime (Block and Block 1993). The general thinking is that gangs uniquely motivate a high level of involvement in violent crime. Violence appears to be central to establishing and maintaining the reputation of gangs and their members, in addition to supporting instrumental goals (Short and Strodtbeck 1964; Luckenbill 1977; McGloin and Collins 2015). Gangs may drive both increased numbers of spontaneous acts of violence (i.e., crimes that occur without any obvious trigger) (Tita et al. 2004) and the contagious spread of events in response to prior acts of violence (Loeffler and Flaxman 2017; Short et al. 2014; Decker 1996). Specifically, gangs may encourage their members to both build on recent successes (i.e., self-excitation), and mount swift reprisals when attacked by rivals (i.e., tit-for-tat retaliation). Contagious violence may be particularly important in the reputational dynamics of gangs if stringing together successes, or hitting back fast and hard, carries greater symbolic value than simply attacking when it is not expected (Lewis and Papachristos 2020). It also is the central theoretical justification for policy interventions that seek to reduce shootings and homicides by 'interrupting' the contagion process (Skogan et al. 2009; Webster et al. 2012; Tremblay et al. 2020).

At the same time, contagious spread of violence does not appear to be strictly limited to gang contexts. It is observed for gun violence in general, both over social networks (Green et al. 2017; Papachristos et al. 2015) and in spatio-temporal crime patterns (Mohler 2014), though the temporal and spatial scale of contagious diffusion may be quite narrow (Loeffler and Flaxman 2017). Violence contagion in non-gang contexts may be rooted in some of the same social processes attributed to gangs including reputation management (Anderson 1999; Jacobs and Wright 2006; Tedeschi and Felson 1994; Mitchell et al. 2017), or it may reflect a generic human preference to simply repeat what has worked in the recent past (Samuelson and Zeckhauser 1988). Thus, it is important to assess the degree to which contagious spread of gang-related violence is distinctive from that of non-gang violence. Assessing such differences is important for understanding the scope of group-level social processes that underlie gangs (Thornberry et al. 1993; Decker et al. 2013). It is possible that group-level social processes increase the frequency of spontaneous (non-contagious) acts of violence, but do not amplify the contagious spread of violence above and beyond what is the case for non-gang violence. As a matter of policy, finding that contagious spread of violence is similar across gang-related and non-gang crimes would suggest that 'violence interruption' could be applied more broadly. Finding that gang-related crimes are more contagious would provide further justification for limited use of resources to treat gang-related events most likely to trigger future crimes. Accurately distinguishing between gang-related and non-gang crimes would then be of added importance.

We test for differences in the contagious spread of violence using a data set of gang-related and non-gang aggravated assaults and homicides from Los Angeles, CA. A multivariate self-exciting point process model allows us to simultaneously estimate clustering due to non-contagious background heterogeneity and that due to contagious diffusion for both gang-related and non-gang crime (see Loeffler and Flaxman 2017). Similar methods have been used previously to study spatio-temporal patterns in property crime (Mohler et al. 2011, 2015) and violent crime (Stomakhin et al. 2011; Short et al. 2014; Green et al. 2017; Mohler 2014). The key contribution here is the use of a multivariate point process model that allows us to estimate contagious spread both within and between crime contexts. Specifically, we are able to examine cross-triggering between gang-related and non-gang crime, where violence contagiously spreads between non-gang and gang-related contexts. We find that gang-related violence triggers twice as many contagious offspring events as non-gang violence and there is little or no cross-triggering. We also find that gang-related contagious offspring events are significantly more lethal than non-gang offspring events, but no more lethal than (non-contagious) background gang crimes.

Methods

Univariate Point Processes

The idea that crime spreads or diffuses contagiously has a long history in criminology. It is closely connected to ideas of event dependence (Farrell and Pease 1993) and contagion is generally thought to contribute to spatio-temporal clustering of crime (Loeffler and Flaxman 2017; Johnson et al. 2007). Decker (1996) explicitly defines violence contagion as "subsequent acts of violence caused by an initial act" (see also Loftin 1986). Retaliatory gang violence is perhaps the most intuitive example of contagious violence; one gang striking back in response to a prior attack (i.e., A attacks B, then B attacks A) (McGloin and Collins 2015). Repeated attacks by the same gang against one or more rivals can also be contagious, if an earlier attack by a gang creates the incentive to mount another attack aimed at the same or a different rival (i.e., A attacks B, then A again attacks B or attacks C) (Papachristos 2009; Lewis and Papachristos 2020). Similarly, cascades of violence across a network of gangs can also be self-exciting if the victim of an attack responds by attacking a third gang (i.e., A attacks B, then B attacks C) (Papachristos et al. 2013; Randle and Bichler 2017; Lewis and Papachristos 2020). Indirect contagion is also possible if knowledge of a crime between two rivals prompts a gang to mount an attack against yet another rival (i.e., A attacks B, then C attacks D). In all of these hypothetical cases, however, the causal dependence between events is expected to generate clustering of those events in space and time.

Different statistical methods have been used to detect and characterize contagion from observed clustering of events (Short et al. 2009; Mantel 1967; Aral et al. 2009; Mohler et al. 2011; Diggle et al. 2005; Ogata 1998; for a review see Loeffler and Flaxman 2017). Decker's definition of violence contagion particularly lends itself to evaluation using self-exciting point process models. Such models minimally take into consideration the discrete time and location of crime events and estimate the degree to which clustering of crime events is the result of: (1) relatively stable, spatial heterogeneity in local risk factors; and (2) local spatial and temporal dependencies among offenses (Heckman 1991; Tseloni and Pease 2003; Loeffler and Flaxman 2017). A generic self-exciting point process model describes the conditional intensity of violent crime at location x, y at time t as:

$$\lambda(x, y, t) = \mu(x, y) + K \sum_{x_i, y_i, t_i} g\left(x - x_i, y - y_i, t - t_i\right) \tag{1}$$

The conditional intensity $\lambda(x, y, t)$ may be interpreted as the expected instantaneous rate of crime at a given location. The model partitions the conditional intensity into two parts. The background intensity $\mu(x, y)$ is stationary in time (i.e., it does not include t), but potentially varies from one location to another (i.e., it includes x, y). Self-excitation is described by a so-called "triggering kernel" g that is dependent on the history of events occurring in space and time (i.e., it includes x, y and t). A parameterization of the generic model for the multivariate case is introduced below.

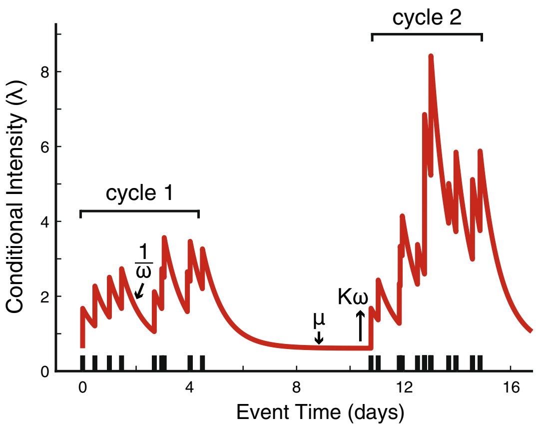

Fig. 1 A temporal self-exciting point process model fit to gang-related violent crimes in South Los Angeles over a two-week period in 2016

In the absence of self-excitation, the conditional intensity in Eq. (1) defaults to a spatially inhomogeneous Poisson arrival process (Daley and Vere-Jones 2003). In other words, risk may vary from place to place, but events occurring *within* each place are expected to be Poisson distributed in space and time. Self-excitation adds a contagion-like mechanism to this baseline. It allows past events $i = 1, 2, \ldots N$ to influence the risk that a new event will occur. The parameter K is called the *productivity* of the self-exciting point process. It is the average number of offspring events triggered contagiously by any one parent. Figure 1 illustrates how the clustering of events (in time) is statistically connected to contagious self-excitation.

Multivariate Point Processes

Past applications of self-exciting point process models to crime have considered clustering in single event types (Mohler et al. 2011; Loeffler and Flaxman 2017). Indeed, the term "self-exciting" refers to the idea that an event of one type (e.g., gang violence) triggers one or more events of the self-same type. Clearly, gang-related violent crime does not occur in a vacuum. Gang-related crimes happen alongside non-gang violent crimes and each may mutually influence the contagious spread of new crimes. Gang-related and non-gang violent crimes can be thought of as following their own point process. In addition, we can model how these point processes interact with one another. The multivariate counterpart to Eq. (1) gives the conditional intensity for crime type u as:

$$\lambda_u(x, y, t) = \mu_u(x, y) + K_{u_i u} \sum_{t_i < t} g\left(x - x_i, y - y_i, t - t_i\right). \tag{2}$$

As in the univariate case, Eq. (1) includes a spatially inhomogeneous background rate $\mu_u(x, y)$ for each crime type u. The self-exciting triggering kernel g now specifies a productivity $K_{u_i u}$, which is the average number of offspring of type u triggered contagiously by a crime of type u_i. The fully specified model with the background rate and self-exciting kernel is:

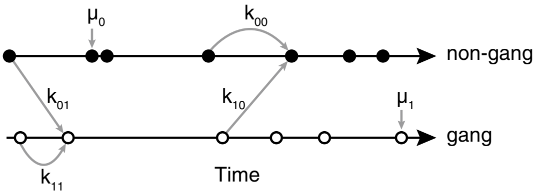

Fig. 2 Background rates and triggering pathways linking gang-related and non-gang crimes over time. Non-gang and gang-related crimes are assigned to two interacting point processes operating over time and space. Only the time dimension is shown

$$\mu_u(x, y) = \sum_{i=1}^{N} \frac{\beta_{u_i u}}{2\pi\eta^2 T} \times \exp\left(-\frac{\left(x - x_i\right)^2 + \left(y - y_i\right)^2}{2\eta^2}\right) \tag{3}$$

$$g(x, y, t) = \omega \exp(-\omega t) \times \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 - y^2}{2\sigma^2}\right) \tag{4}$$

In Eq. (3), $\beta_{u_i u}$ is a weights matrix describing how events of type u_i contribute to the background rate for events of type u, η is the typical spatial decay of background risk at increasing distance from location x, y, and T is the total time represented by observed data. In Eq. (4), ω is the temporal decay rate associated with self-excitation (i.e., the rate at which risk of contagion following a single event returns to the background risk), and σ is the spatial decay of elevated risk associated with self-excitation with increasing distance from location x, y (i.e., a near-repeat spatial effect).

Our primary interest is in the multivariate productivity $K_{u_i u}$ from Eq. (2). For the case of interacting gang-related and non-gang violent crimes, $K_{u_i u}$ is a matrix with four entries. If we label gang-related violent crimes with $u = 1$ and non-gang violent crimes with $u = 0$, then entry k_{11} in $K_{u_i u}$ is the average number of gang-related offspring crimes triggered by a single gang-related parent. This is violence contagion *within* gang contexts (i.e., a gang-related violent crime triggers one or more additional gang-related violent crimes). Entry k_{01} is the average number of gang-related offspring triggered by any one non-gang parent crime. This is contagion *from* non-gang *to* gang contexts. Contagious cross-triggering of this sort might describe crimes in a social context not explicitly tied to gangs (e.g., a dispute over money or love interests), but brings the broader gang apparatus to bear (e.g., as a form of escalation via friends or family). Entry k_{00} is the average number of non-gang offspring crimes triggered by a single non-gang parent crime. This is contagion *within* non-gang contexts. It may cover contagion among crimes following some generic form of "street justice," independent of gang dynamics. Finally, entry k_{10} is the average number of non-gang offspring crimes triggered by any single gang-related violent crime parent. This is contagion *from* gang *to* non-gang contexts. We might expect this triggering pathway if gangs do not take a special interest in a prior crime committed against them, thus leaving it to an individual to resolve the problem himself.

Figure 2 provides a conceptual illustration of these interactions in a network framework. Background, non-contagious events are identified without a causal arrow from any prior event. These are events generated by a Poisson process with parameters μ_1 and μ_0 corresponding to gang-related and non-gang crimes, respectively. Contagious self-excitation is identified by events with a causal arrow arising from a prior event. The causal arrows connect events that are either of the same type (i.e., self-excitation), or between types (i.e., cross triggering).

Model Estimation and Statistical Testing

Modern statistical methods allow simultaneous estimation of the background and self-excitation components of the conditional intensity exposing the unique effects of contagion (see Loeffler and Flaxman 2017). We use a version of Poisson log-likelihood estimation (MLE) called Expectation–Maximization to estimate the multivariate model (Lewis and Mohler 2011). The details of implementation are discussed in the Appendix. We use the Wald test (Z) to evaluate if parameter estimates are different from zero (Fox 1997) and also to compare triggering estimates across models (see also Paternoster et al. 1998).

Stochastic Declustering

Below we will have an interest in labeling specific events as background or contagious crimes. Stochastic declustering is a suite of methods developed in the study of earthquake catalogs where the goal is to distinguish between background seismicity and aftershocks (Zhuang et al. 2002). The same methods can be applied to the study of crime (Mohler et al. 2011). Starting with a self-exciting point process model with parameters fit to a given data set, stochastic declustering proceeds through a thinning procedure that removes events probabilistically classified as retaliations. The events remaining after thinning represent the background events generated by a spatially non-homogeneous Poisson process $\lambda(t, x, y) = \mu(x, y)$. In the univariate spatio-temporal case, the probability ρ that an event j is a retaliation is given by:

$$\rho_j = \frac{\sum_{t_i<t_j} g\left(x_j - x_i, y_j - y_i, t_j - t_i\right)}{\lambda\left(x_j, y_j, t_j\right)}. \tag{5}$$

Intuitively, the numerator is the cumulative contribution of self-excitation from all prior events i to the instantaneous intensity that generated event j. In Fig. 1, if we take j to be the last event in cycle 2, then $g = 0$ for all of the events in cycle 1, which contribute nothing to the probability that j is a retaliation. The first ten events in cycle 2 have $g > 0$ and therefore each contributes something to the probability that j is a retaliation. The ratio of $\sum g$ to λ is the proportion of the conditional intensity underlying event j that is due to self-excitation. The ratio therefore acts like an empirical probability. The probability that an event j is a background event is therefore:

$$1 - \rho_j = \frac{\mu\left(x_j, y_j\right)}{\lambda\left(x_j, y_j, t_j\right)}. \tag{6}$$

For a catalog of N total crimes, the simplest stochastic decluttering procedure is to generate N uniform random variables $U_1, U_2, \ldots, U_N$ in the range (0, 1] and classify a crime j as a background crime when $U_j < 1 - \rho_j$, otherwise classify it as a retaliation (Zhuang et al. 2002). Since each declustering, computed for the catalog of N total crimes, is a realization of a stochastic process (like a Monte Carlo simulation), we repeat the stochastic declustering 1000 times to compute the mean and standard deviation of the estimated number of background crimes and retaliations. We use stochastic declustering to consider differences in lethality of both non-gang and gang-related background crimes and retaliations.

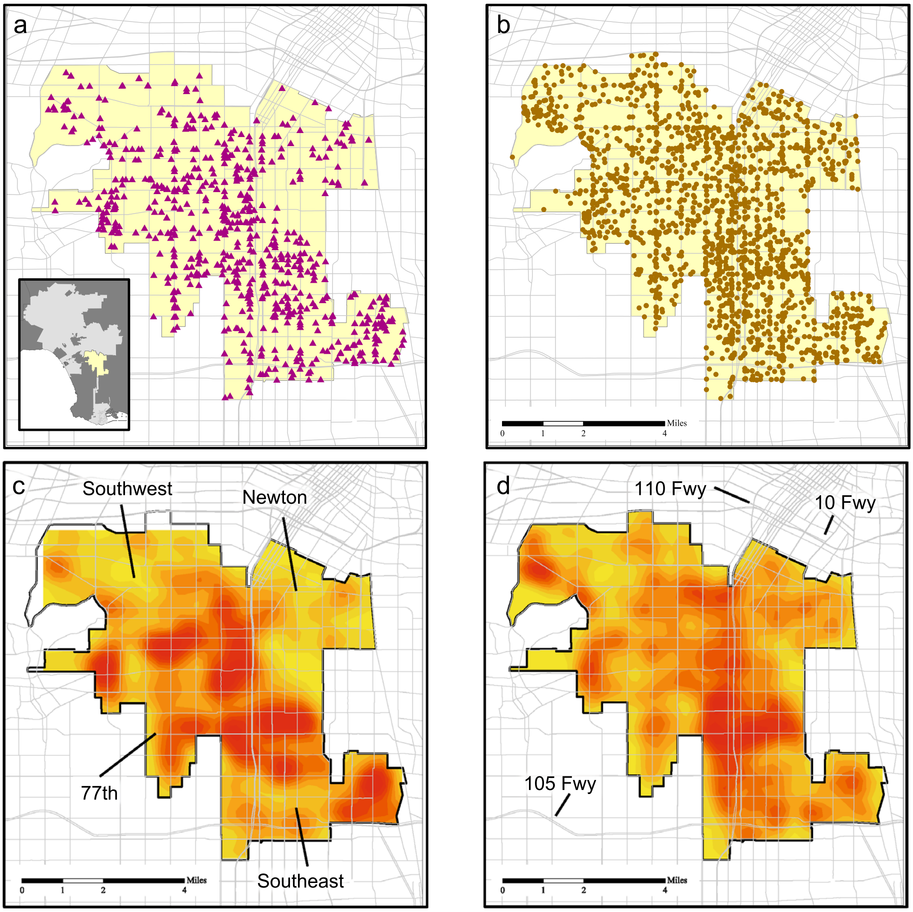

Fig. 3 Aggravated assaults and homicides in South Los Angeles in 2016. **a** and **c** Gang-related violent crimes. **b** and **d** Non-gang violent crimes. Shaded area shows the region serviced by the Los Angeles Mayor's Office of Gang Reduction Youth Development. LAPD Divisions are indicated in (**c**). Locations of the 10, 105 and 110 Freeways are indicated in (**d**)

Data

Violent crime data from Los Angeles were used in this study. Analyses were restricted to the 3071 aggravated assaults and 71 homicides that occurred in an 87.2 km^2 area of South Los Angeles during 2016 (Fig. 3, Table 1). The region encompasses ten geographic areas serviced by the Los Angeles Mayor's Office of Gang Reduction Youth Development (GRYD). GRYD is a comprehensive prevention, intervention and violence intervention

Table 1 Aggravated assaults and homicides in South Los Angles during 2016

	Non-gang		Gang-related		Total
	N	%	N	%	N
Aggravated assault	2196	71.5	875	28.5	3071
Homicide	15	20.3	59	79.7	74
Total	2211	70.3	934	29.7	3145

program (Tremblay et al. 2020). The ten areas overlap with all or part of the Los Angeles Police Department's (LAPD) Southwest, Newton, 77th and Southeast Patrol Divisions.[1] The data used in the analyses were provided by the LAPD and include only crimes reported to the police. Homicide is reported with close to perfect accuracy. National figures suggest that approximately 60% of aggravated assaults are reported on average (Morgan and Oudekerk 2019). Crime underreporting may have a neutral or biased effect on detection of the contagious spread of crime. For example, if retaliatory gang crimes were systematically more (less) likely to be reported than background gang crimes, then the contagious spread of crime would appear to be stronger (weaker) than it actually is (see Loeffler and Flaxman 2017). We return to this issue in the Discussion.

The LAPD distinguishes between gang-related and non-gang crimes for a wide range of crime types including homicide, assault, rape, robbery, shots fired and carjacking. The LAPD recognizes that the distinction is subjective in nature and must be based on an assessment of the totality of information about a crime. Specifically, the LAPD manual states that: "Any crime may constitute a gang-related crime when the suspect or victim is an active or affiliate gang member, or when circumstances indicate that the crime is consistent with gang activity" (LAPD 2019: §269.10). Relevant circumstances include if the crime occurred within gang territorial boundaries or known gang hangout, and if the *modus operandi* of the crime is inherently gang-related (e.g., drive-by shooting). The area gang officer in charge is nominally involved in determining if any crime is gang related. We are unable to verify the criteria used in the labeling of specific crimes. Prior research suggests, however, that gang involvement of suspects and/or victims tends to be the deciding factor (Maxson and Klein 1990; Rosenfeld et al. 1999). Rosenfeld et al. (1999) would classify such crimes as gang-affiliated. We use gang-related as a more general term since we do not have specific information on the basis for labeling each crime (see Discussion).

Approximately 30% of the aggravated assaults in the study region were identified as gang-related. Approximately 80% of the homicides in the study region were identified as gang related. The next section uses these data to examine differences between gang-related and non-gang in the contagious spread of violent crime.

[1] Excluded from the areas serviced by GRYD are portions of Newton Division northeast of E. Adams Blvd, which represent the Los Angeles Downtown area, and the extension of Southeast Division, south of E. El Segundo Blvd.

Table 2 Estimated parameters and standard errors of the estimates for univariate models fit separately to 2016 data

Parameter[†]	Non-gang estimate (SE)	Gang-related estimate (SE)	Z[††]	*p* value
β	0.880 (0.071)	0.720 (0.071)	−2.191	0.014
K	0.121 (0.062)	0.281 (0.062)	2.558	0.005
ω	1.636 (0.223)	0.647 (0.223)	−1.603	0.054
σ	0.126 (0.003)	0.122 (0.003)	−1.275	0.101

[†]Parameter description: β Estimated influence of background events; K Expected number of triggered offspring per parent event; $1/\omega$ Estimated mean time to a triggered offspring crime; σ Estimated spatial decay for triggering with increasing distance from parental event

[††]Wald statistic comparing gang-related to non-gang parameter estimates for separate models assuming no covariance between estimates

Results

Univariate Model Results

We now fit the univariate spatio-temporal model (Eq. 1) to the gang-related and non-gang crimes separately (see Appendix). The estimated model parameters along with standard errors are shown in Table 2. The parameters β and K represent the contributions of background and contagion processes, respectively, to the spatio-temporal occurrence of crime. We use subscripts 1 and 0 to reference parameter estimates for gang-related and non-gang crime respectively. The values of β indicates that background processes play a greater role (+22%) in generating non-gang crimes than gang-related crimes. The parameter K is a measure of the expected number of contagious offspring events (e.g., retaliations) triggered by any one prior crime. Gang crimes on average trigger two-times more gang-related offspring events compared with non-gang crimes. For every 100 gang-related violent crimes there are an estimated 28.1 gang-related offspring. For every 100 non-gang violent crimes there are an estimated 12.1 non-gang offspring (Table 2). All of the parameter estimates are significantly different from zero (results not shown). The background rate for non-gang crimes is significantly higher than for gang-related crimes ($\beta_1 - \beta_0 = -0.16, Z = -2.191,\ p = 0.014$) (Table 2). The triggering rate for gang-related offspring is significantly higher than for non-gang offspring ($K_1 - K_0 = 0.160, Z = 2.558, p = 0.005$) (Table 2).

Contagious triggering also occurs over a longer period of time for gang crimes. The half-life of contagion is given as $\ln(2)/\omega$. This means that 50% of gang-related contagious offspring occur on average within $\ln(2)/0.647 = 1.07$ days of a triggering event. Ninety percent of gang-related offspring occur within 7 days of a triggering event. By contrast, 50% of non-gang contagious offspring occur on average within $\ln(2)/1.636 = 0.424$ days of the triggering event. Ninety percent of non-gang offspring occur within 3 days. The difference is marginally insignificant ($\omega_1 - \omega_0 = -0.989, Z = -1.603, p = 0.054$). The spatial region over which background and contagion processes operate is given by σ^2 and is approximately the same for both gang and non-gang crimes. The difference is insignificant ($\sigma_1^2 - \sigma_0^2 = -0.004, Z = -1.275, p = 0.101$).

Table 3 Estimated parameters and standard errors of the estimates for the multivariate model of non-gang and gang-related crimes

Parameter[†]	Estimate	SE	Z[††]	p-value
β_{11}	0.836	0.449	1.862	0.031
β_{10}	2.057	0.647	3.18	0.001
β_{00}	0.074	0.254	0.293	0.385
β_{01}	4.11E−07	0.187	2.20E−06	0.5
k_{11}	0.164	0.035	4.724	<0.0001
k_{10}	8.14E−06	0.06	1.36E−04	0.5
k_{00}	0.113	0.063	1.797	0.036
k_{01}	3.14E−04	0.027	0.012	0.495
ω	2.282	1.082	2.109	0.017
σ	0.125	0.002	77.443	<0.0001

[†]Parameter descriptions: β_{ij} Estimated influence of events to type i on the background rate for events of type j; k_{ij} Expected number of offspring events of type j triggered by events of type i; $1/\omega$ Estimated mean time to a triggered offspring crime; σ Estimated spatial decay for triggering with increasing distance from parental event

[††]Wald statistic testing parameter estimate against the null hypothesis that the true parameter is zero

Multivariate Model Results

The multivariate model provides an opportunity to estimate interactions effects between crimes labeled as non-gang and gang-related. Table 3 presents the results. The interpretation of the parameter β_{ij} is more complicated in the multivariate case. Here β_{ij} gives the degree to which background processes associated with events of type i contribute to the occurrence of events of type j. For example, β_{11} is the degree to which gang-related background processes contribute to gang-related background crimes, while β_{01} is the degree to which non-gang background processes contribute to gang background crimes. The matrix of β_{ij} values is highly asymmetrical. Non-gang background processes make insignificant contributions to the occurrence of both non-gang $\left(\beta_{00} = 0.0074\right)$ and gang-related crimes $\left(\beta_{01} = 4.1 \times 10^{-7}\right)$. The standard errors indicate that neither parameter estimate is significantly different from zero $(\beta_{00} : Z = 0.293, p = 0.385; \beta_{01} : Z < 0.001, p = 0.5)$ (Table 3). By contrast, gang-related background processes make a noticeable contribution to the occurrence of gang-related crimes $\left(\beta_{11} = 0.836\right)$, and a massive contribution to the occurrence of non-gang crimes $\left(\beta_{10} = 2.057\right)$. The standard errors indicate that these are significantly different from zero $(\beta_{11} : Z = 1.862, p = 0.031; \beta_{10} : Z = 3.18, p < 0.001)$ (Table 3). In other words, background processes underlying gang violence appear to create stationary conditions that support the occurrence of both gang and non-gang violence. This observation is consistent with the idea gangs produce a "lawlessness" that allows both gang and non-gang to thrive (Leovy 2015; Lane and Meeker 2003).

Interpretation of the contagious interactions between processes for gang-related and non-gang crimes proceeds in similar manner (Table 3). The parameter k_{11} is the average number of gang-related contagious offspring triggered by a single prior gang-related crime. The parameter k_{00} is the average number of non-gang contagious offspring triggered by a prior non-gang crime. Comparing these two values shows that contagion is more common among gang-related crimes (i.e., $k_{11} = 0.164 > k_{00} = 0.113$). For every 100 gang-related crimes

Table 4 AIC values for models with and without retaliation

	Poisson AIC	Self-exciting AIC
Univariate non-gang	−2775.73	−7165.22
Univariate gang-related	366.82	−1444.60
Multivariate	−2408.92	−8611.85

Table 5 Number of background crimes and retaliations determined by stochastic declustering

	Non-gang		Gang-related		Total	
	N (SE)	%	N (SE)	%	N	%
Background	1769.4 (14.0)†	88.7	658.6 (9.7)	83.6	2428.0	87.2
Retaliation	225.6 (14.0)†	11.3	129.4 (9.7)	16.4	355.0	12.8
Total N	1995		788		2783‡	

†Standard errors are the same since the probability that an event is background is complementary to the probability that it is a retaliation

‡The total number of crimes is lower due to uncertainty in geolocation

there are an additional 16.4 gang-related contagious offspring. For every 100 non-gang violent crimes there are 11.3 non-gang contagious offspring. Gang-related crimes produce about 45% more gang-related offspring on average. The results are attenuated compared with the univariate models. In both cases, the parameters are significantly different from zero ($k_{11} : Z = 4.724, p < 0.0001; k_{00} : Z = 1.797, p = 0.036$). However, the difference between the parameter estimates is insignificant ($k_{11} - k_{00} = 0.051, Z = 0.704, p = 0.24$).

There is very limited interaction between non-gang and gang-related crimes. The parameter k_{01} gives the average number of gang-related offspring triggered by a prior non-gang crime. The estimate for this parameter is three orders of magnitude smaller than is seen for offspring triggered strictly within non-gang crimes (i.e., $k_{00} = 0.113 > k_{01} = 0.0003$). We interpret this to mean that non-gang crimes *may* trigger gang-related retaliations, but this is a very rare occurrence indeed. Whereas every 100 non-gang violent crimes trigger an additional 11 non-gang retaliations, it takes 10,000 non-gang crimes to trigger 3 gang-related retaliations. The parameter k_{10} describes the average number of non-gang contagious offspring triggered by a single gang-related crime. The estimate $k_{10} = 8.14 \times 10^{-6}$ suggests that gang-related crimes effectively *never* trigger non-gang offspring. In both case, the parameters for cross-triggering are not significantly different from zero ($k_{01} : Z = 0.012, p = 0.495; k_{10} : Z = 1.36 \times 10^{-4}, p = 0.5$) and the parameters are not significantly different from one another ($k_{01} - k_{10} = 0.003, Z = 0.0046, p = 0.498$).

Model Parsimony

An important question concerns whether contagion is important for describing the spatio-temporal dynamics of gang-related and non-gang crime. To evaluate this question, we use the Akaike Information Criterion (AIC) (Akaike 1974) to compare models. Specifically, we compare models where $\lambda(t) = \mu + g$ to alternative, simpler models where $\lambda(t) = \mu$. The only difference is the inclusion of contagion in the former. The latter assumes that events are generated by a stationary Poisson process only. AIC seeks to balance model parsimony against model fit. In general, we prefer simpler models as long as they offer a reasonable

Table 6 Number of background crimes and retaliations by crime type

	Aggravated assault		Homicide		Total
	N (SE)	%	N (SE)	%	
Non-gang					
Background	1759.6 (14.1)†	88.7	9.8 (0.8)	89.0	1769.4 (14.0)
Retaliation	224.5 (14.1)†	11.3	1.2 (0.8)	11.0	225.6 (14.0)
Total N	1984		11		1995
Gang-related					
Background	611.4 (9.2)	83.8	47.2 (2.8)	81.3	658.6 (9.7)
Retaliation	118.6 (9.2)	16.2	10.8 (2.8)	18.7	129.4 (9.7)
Total N	730		58		788

†Standard errors are the same since the probability that an event is background is complementary to the probability that it is a retaliation

fit to the data. The more complex model provides a preferred description of the data (i.e., more negative AIC values) (Table 4). Even though stationary, background processes produce many more crimes than contagion processes, leading to an expectation of a good fit to the simpler model, contagion appears to be integral to both gang-related *and* non-gang violent crime dynamics.

The Lethality of Gang-Related Retaliations

Both the univariate and multivariate Hawkes models can be used to perform stochastic declustering of individual crime events (Zhuang et al. 2002). This method allows us to probabilistically label each event in the dataset as either a background crime or contagious offspring (e.g., retaliation). Table 5 reports the estimated numbers of background crimes and offspring for 1000 repeated declustering runs. Because stochastic declustering assigns labels probabilistically, these can change somewhat from one declustering run to another. Table 5 therefore also reports standard errors of the estimates. The numbers in Table 5 can be interpreted like expected values of the outcome variable from a regression model. Consistent with reported model parameters, the estimated number of background crimes exceed the estimated number of retaliations by at least 5:1, but the estimated number of contagious offspring comprise a much greater fraction of the gang-related violent crimes (16.4%) compared to non-gang violent crimes (11.3%).

Table 6 shows the estimated number of aggravated assaults and homicides each probabilistically classified as background crimes or contagious offspring. Approximately 0.6% (9.8 of 1769.4) of the non-gang background crimes are homicides. Similarly, 0.5% (1.2 of 256.6) of the non-gang contagious offspring are homicides. By contrast, 7.2% (47.2 of 658.6) of the gang-related background crimes are homicides. Approximately 8.3% (10.8 of 129.4) of the gang-related offspring are homicides. Gang-related background crimes are significantly more lethal than non-gang background crimes (+6.6%, pooled proportion test: $Z = 9.57$, $p < 0.0001$). Gang-related contagious offspring are significantly more lethal than non-gang contagious offspring (+7.8%, $Z=3.9$, $p < 0.0001$). Non-gang contagious offspring are not more lethal than non-gang background crimes (−0.02%, $Z=-0.04$, $p = 0.52$). Gang-related offspring are fractionally more lethal gang-related background crimes, but the difference is not statistically significant (+1.2%, $Z=0.47$, $p = 0.32$). That there is not a greater jump in lethality associated with contagion in gang contexts is perhaps a reflection of the greater prevalence of gun usage in gang-related violent crimes (Maxson et al. 1985; Bjerregaard and Lizotte 1995; Huebner et al. 2016).

Discussion

The present study uses multivariate self-exciting point-process models to detect and characterize violence contagion in gang-related and non-gang crimes. We emphasize several key findings. First, background crimes are numerically dominant for both gang and non-gang contexts. This is seen most clearly in the stochastic declustering analyses where background crimes make up approximately 89% of non-gang and 84% of gang-related violent crimes, respectively (see Table 5). Second, we found some evidence that gang-related violent crime is more contagious than non-gang crime. In the univariate model, any one gang-related crime on average triggers around twice as many contagious offspring events as any one non-gang crime. In the multivariate model, any one gang related violent crime triggers around 1.5 times as many contagious offspring as non-gang violent crime. The difference is statistically significant for the univariate models, but insignificant for the multivariate model with interactions. Third, the risk of contagious spread associated with each gang-related crime lasts about twice as long as for any one non-gang crime, though the time scale associated with triggering is very short in both cases (see also Loeffler and Flaxman 2017). Fourth, while gang-related violent crime is more lethal than non-gang violent crime, there is no significant difference in the lethality of gang-related background crimes compared to gang-related contagious offspring (e.g., retaliations). Finally, we found that cross triggering between non-gang and gang-related violence is rare to non-existent.

The Uniqueness of Gang-Related Crime

Overall, our results align with several decades of research documenting many differences between gang-related and non-gang crime. Research has shown that gang crime tends to be more violent than non-gang crime and is more likely to involve the use of firearms (Bjerregaard and Lizotte 1995; Pyrooz et al. 2016; Huebner et al. 2016; Block and Block 1993). Gang homicides are more likely to take place in public settings and involve multiple participants (Maxson et al. 1985). While the participants in gang assaults and homicides are less likely to know one another, they tend to resemble one another in demographic and socio-economic characteristics to a substantial degree (Pyrooz et al. 2014). Gang offenders and victims are typically young, male and from socio-economically disadvantaged backgrounds (Maxson et al. 1985; Rosenfeld et al. 1999). Beyond setting and participant characteristics, gang violence is markedly concentrated in disadvantaged neighborhoods compared with non-gang violent crime (Papachristos and Kirk 2006; Valasik et al. 2017) and proximity to neighborhoods with a high density of gang membership tends to increase gang violent crime above and beyond the influence of structural factors (Huebner et al. 2016). Across cities, the volume of gang violence is associated with differences in social and economic deprivation, while non-gang violence more generally tracks differences in population density (Pyrooz 2012).

The models and analyses presented here suggest that gang-related violence is also more contagious than non-gang violence. This result is consistent with research documenting the prevalence of retaliation in gang-related and non-gang homicides. Maxson et al. (1985)

noted that fear of retaliation was a feature in 33% of the gang homicides they studied, but also in 10% of the non-gang homicides. Kubrin and Weitzer (2003) looked at differences between retaliatory and non-retaliatory homicides over a 10-year period in St. Louis, MO. Of 1731 crimes with documented motive, 337 (19.5%) were deemed retaliatory. Nearly 28% (60 of 216) of the recorded gang homicides were retaliatory. However, approximately 23% (144 of 622) of drug-related homicides and 18% (114 of 645) of alcohol-related homicides were also deemed retaliatory. While Kubrin and Weitzer's (2003) crime categories were not mutually exclusive—some of the 144 drug-related crimes may have also been counted among the 60 gang-related crimes—they show that retaliatory violence is not limited to gang contexts. Our findings provide some measure of how different the contagious spread is in gang-related aggravated assaults and homicides and how limited the degree of interaction with non-gang violent crimes may be.

Implications for Theory

The results presented here are relevant to understanding the group-level processes associated with gangs. The general consensus is that gangs create both unique offending opportunities and motivate the use of violence to achieve instrumental and symbolic goals (Klein and Maxson 2006; Decker et al. 2013). Unique offending opportunities emerge out of neighborhood-based gang territoriality (Brantingham et al. 2012; Tita et al. 2005), gang sanctioned unstructured social routines (Melde and Esbensen 2011), and ready access to guns via gang social networks (Roberto et al. 2018). These processes influence the spatial structure of gang activity patterns, enhance the control that gangs exert over space, and reduce the barriers to violent engagement. Gangs may motivate the use violence to achieve instrumental goals such as controlling elicit markets (Taniguchi et al. 2011). However, indiscriminate violence is generally seen as detrimental to corporate goals and may be a signature of "disorganized" gangs (Klein et al. 1991; Decker and Van Winkle 1994). More importantly, gangs appear to motivate the use violence to establish and maintain reputation, both for individual gang members and the gang as a whole (Short and Strodtbeck 1964; Luckenbill 1977; Decker 1996; Lewis and Papachristos 2020).

Our findings support a conclusion that group-level processes amplify the dynamics of gang-related violence. Gang-related violence is more contagious than non-gang violence by a factor of 1.5–2 based on the multivariate and univariate models, respectively. However, gang-related contagious offspring (e.g., retaliations) are *not* more lethal than gang-related background gang crimes. This is an important observation in the context of Decker's (1996) escalation hypothesis, where the group-level processes of gangs make it more likely that an argument leads to a battery, a battery to a shooting, and a shooting to a homicide (see also Matsuda et al. 2013). If we assume that escalation is inherently a contagious process, then it may be seen as problematic that there is not a substantial ratcheting up of lethality with contagious aggravated assaults. A possible explanation for our results is that most gang-related shootings are attempted homicides. Thus, both background and contagious aggravated assaults already represent the peak of escalation. If a shooting ends up as a successful homicide with some fixed probability, then the lethality of background and contagious gang-related violent crimes should be roughly the same. Valasik (2018), by contrast, argues that gang-related aggravated assaults are more likely to be spontaneous and homicides more likely to be planned, which might imply a that contagious events should be more lethal.

The finding that cross triggering between non-gang and gang-related violence is rare to non-existent reinforces the idea that gang-related violent crimes are dynamically unique. The limited "spillover" between contexts might be surprising given ethnographic accounts that individuals move between non-gang and gang social roles with ease (Patillo-McCoy 1999; see also Smith and Papachristos 2016). We might expect that frequent switching among social roles would create many opportunities cross-triggering, even if the "spillover" was accidental. One possible explanation for our results is that individuals and their social groups (gang and non-gang) operate under a heuristic that attempts to keep gang-related and non-gang motives quite separate. In other words, individuals may simply "know" which crimes require a gang-related response and which do not. It is also possible that unaffiliated victims of gang-related crime have limited recourse to retaliate (Papachristos 2009; Leovy 2015). A definition of gang-related crime based on the affiliation of victims and/or suspects may also limit the amount of observable cross triggering. Specifically, since it only takes only one participant (suspect or victim) to label an event as a gang-related crime, it may be that the gang-related context soaks up all crimes that have even a tenuous relationship to gangs (see Maxson and Klein 1990; Rosenfeld et al. 1999; Maxson and Klein 1996). The multiplexity of social roles is washed out by an affiliation-based definition of gang crime. The crimes remaining thus may be truly independent of gang dynamics and therefore should be expected to display limited cross-triggering.

The present paper encourages us to think about crime in probabilistic terms. We cannot say that one crime was definitively the cause of another, only that knowing about one crime helps predict a future crime (see Granger 1988). Nevertheless, we do assign events to background and offspring crime categories using stochastic declustering and report expected values over repeated declustering runs (see Zhuang et al. 2002). The resulting probabilistic assignments could invite comparisons with other sources of information about the corresponding crimes (e.g., Kubrin and Weitzer 2003). These may align closely. However, conflicts might arise if inspection of case records produces evidence that contradicts probabilistic labeling. It is difficult to know what to do with such contradictions. If an event presents statistical dependence sufficient to count it as a contagious offspring, but narrative evidence suggests otherwise, which labeling are we to believe? Confounding variables might be responsible for producing apparent statistical dependence for events that are in fact not contagious (Loeffler and Flaxman 2017). Alternatively, a crime might indeed be the product of contagion, but this motive may be hidden from those compiling a narrative of the crime. What are we to do if the narrative suggests a crime is a contagious retaliation, yet there is no evidence of statistical dependence? If the events are non-local (in space), then the absence of statistical dependence might be understandable (see below). Alternatively, the narrative might be biased towards some theory of the crime based on spurious evidence. We do not see these challenges as limitations per se. Rather they point to an important area of empirical research. Such research might include a careful comparison of the results of statistical modeling efforts alongside detailed review of case files. It also suggests that there is room for hybrid approaches that introduce covariate information from case files into self-exciting point process models to try to control for other causal pathways connecting events (Sha et al. 2020; Mohler and Brantingham 2018; Liu et al. 2020).

Finally, we note that the multivariate models presented here could assess the degree of interaction between other event types hypothesized to be ecologically similar. For example, the so-called "broken windows" theory of crime posits in part that misdemeanor crimes support felonies (Wilson and Kelling 1982). Crime types could interact via a long term (slowly evolving) process that shows up as environmental heterogeneity in the short term, or via short-term triggering; this distinction would be between misdemeanors creating general conditions that encourage felonies, or misdemeanor vandalism events triggering specific burglaries. The models presented here could help identify both possibilities. Specifically, in a multivariate model, the entries in β provide information on how different crime types contribute jointly to environmental heterogeneity. The entries of K provide information of whether there is cross-triggering between misdemeanors and felonies of interest. Importantly, while the models developed here examined a multivariate case with only two crime contexts, one could theoretically include a full suite of crime types. Such analyses may confirm expected relationships between certain crime types, but also identify unexpected relationships between crime types thought to be independent, or independence of crime types thought to be connected (see Kuang et al. 2017).

Implications for Policy

Contagious events such as tit-for-tat gang retaliations present clear tactical target for intervention. That an event may be triggered by one or more prior events provides important information that can be used to gain an intervention advantage. Indeed, we can think of the statistical dependencies inherent to the contagious spread of violence as the basis of an "early warning system" to be used by police or civilian interventionists (see Mohler et al. 2011, 2015; Green et al. 2017; Loeffler and Flaxman 2017). Knowing how likely a contagious offspring event is to occur, how quickly it will occur and over what spatial domain, may allow for concentrated efforts to disrupt those retaliations. In the present case, for example, the estimated half-life of approximately 1 day for gang-related contagious offspring (e.g., retaliations) provides some indication of just how rapid the response time needs to be for of violence interruption efforts (Skogan et al. 2009; Whitehill et al. 2014; Tremblay et al. 2020). The first twenty-four hours appears to be crucial. However, while the contagious spread of violence is more common when gangs are involved, it is still quite a prominent feature of non-gang violent crime. Indeed, researchers may be more surprised at the level of contagious triggering in non-gang contexts than the conclusion that gang-related violence is more contagious. While we might expect some level of violence contagion in non-gang crime in street settings, we might also expect that greater diversity of non-gang violent crime settings (e.g., domestic, workplace) would dilute observed triggering. At this time, we cannot distinguish differences between settings at a scale to evaluate impact on the models. In any case, the results presented here suggest that there may be room for violence interruption efforts in a wider array of contexts, even if there is not a clear connection to gangs.

It is important to remember, however, that contagious offspring events comprise only a minority fraction of violent gang (and non-gang) (see also Loeffler and Flaxman 2017). In our study area, for example, only 16% of the gang-related homicides and aggravated assaults are probabilistically identified as the product of contagion (see Table 5). The remaining 84% are background events. Thus, violence interruption programs can only hope to directly impact a small fraction of all gang crimes, and an even smaller fraction of non-gang violent crimes. Background crimes are more challenging to deal with. These emerge out of a complex mix of cultural norms, patterns of social interaction, and structural environmental conditions (Valasik 2018; Mitchell et al. 2017; Huebner et al. 2016; Pyrooz 2012; Melde and Esbensen 2013). It is difficult, if not impossible to physically preempt background crimes "in the moment," since there are just not enough resources (law enforcement or community-based) to be in all of the combustible situations that might spontaneously generate a crime. Background crimes therefore may be more appropriately addressed by prevention measures that seek to alter the very nature of social and environmental conditions underlying such events. When conditions do converge in particular context, it is hoped that prior prevention efforts limit their combustibility. For example, focused deterrence strategies or injunctions that target gangs as groups (Braga et al. 2018; Ridgeway et al. 2019) may indirectly alter the situational calculus underlying background crimes (as well as contagious spread). Going after deeper "root causes," such as individual developmental risk factors or neighborhood structural disadvantage, is both complex and challenging, but may nevertheless yield long-term benefits (Sharkey, Torrats-Espinosa, and Takyar 2017; Gravel et al. 2013). Comprehensive violence prevention programs that seek to reduce the risk factors for joining gangs may be thought of as one approach to reducing the potential for background gang crime (see Hennigan et al. 2014, 2015; Tremblay et al. 2020). The analyses presented here suggest that it is ideal target both background and contagious offspring crimes, reaping the benefits of addressing "root causes" and short-term triggers. Comprehensive gang violence reduction programs should therefore benefit by including both prevention and violence interruption efforts, rather than just one or the other.

Limitations and Future Research

The data used in this study rely on distinctions between gang-related and non-gang crime made by the LAPD. Gang-crime measures derived directly from law enforcement sources present both advantages and disadvantages (Melde 2016). Prior research has shown that law enforcement measures of gang-related homicides have internal reliability, pass convergent-discriminant validity tests, and have external validity (Decker and Pyrooz 2010). Cities with specialized gang units, like Los Angeles, also perform better on reliability and validity tests. Whether law enforcement measures of gang-related aggravated assaults perform similarly is unknown at present. Though not intended as a test of convergent-discriminant validity, the results presented here suggest that LAPD's labeling of violent crimes is based on a statistically valid construct. The absence of triggering between gang-related and non-gang violent crimes (i.e., $k_{01} \ll k_{00}$ and $k_{10} \ll k_{11}$) suggests that the labels successfully discriminate between real contextual differences in violent crimes. The substantive triggering among gang-related crimes suggests that the labels are applied to events arising from the same context. The observed results are not what we would expect if labels were applied arbitrarily (see Appendix).

Nevertheless, it is possible that the gang-related and non-gang constructs themselves are systematically biased due to organizational goals (Melde 2016). Recent revelations of alleged police misconduct by LAPD officers in identifying as gang members also raises concern (Miller and Chabria 2020). Biases that influence the labeling of suspects and victims as gang members can impact the labeling of the corresponding crimes. We have no specific information on the prevalence of biased labels in the present data. Future research should carefully assess how the processes that might underlie biased labeling of gang-related crimes operate, the potential impact of biased labels on model performance, how such biases do or do not impact law enforcement outcomes, and ultimately how such biases might be corrected (e.g., Brantingham 2017; Mohler et al. 2018; Brantingham et al. 2018). Initial assessments suggest that crimes are labeled independently of one another as they are reported (see Appendix).

We should be particularly clear about limitations that arise from defining violence contagion in terms of local statistical dependencies estimated through point process models.

Contagious events may also exist via long-range (in time) and non-local (in space) connections between crimes (see Jacobs 2004). For example, a retaliation may be motivated by the anniversary of a past crime. Rivalries fueled in part by online conflict (Storrod and Densley 2017; Pyrooz et al. 2013; Densley 2020; Patton 2019), may encourage conflict between distant neighborhoods. The models used here expect exponential triggering, making it unlikely that non-local temporal and spatial statistical dependencies would be detected. If such long-range and non-local dependencies are rare, then there we expect limited impact on the estimation of the model. If they are common, then non-parametric models may be needed identify such dependencies. Mohler et al. (2011), for example, identify triggering in residential burglary at 3, 7 and 39 day lags, using non-parametric methods, rather than simply as a monotonically decreasing function of time. These are important possibilities that also could be investigated through close examination of case files. We note, however, that retaliation is invoked primarily as an explanation for "sudden peaks in gang violence" (Decker 1996; Decker and Van Winkle 1996), which implies that contagion is viewed predominantly a local, short time-scale processes.

There are also potential limitations associated with the under-reporting of crime. The probabilistic approach in self-exciting point process models traces dependencies between crimes that are known to the police. An unreported argument, burglary, robbery or simple battery that triggers an offspring event cannot be statistically recognized as such. Differences in crime reporting may vary with trust in law enforcement across neighborhoods (Kirk and Papachristos 2011). It is not entirely clear that willingness to report crime varies much between gang-related and non-gang crime (Melde and Rennison 2010). In any case, as long as the underreporting probability is the same for triggering crimes (parents) and offspring, then estimates of triggering parameters are not biased (Daley and Vere-Jones 2003), or are impacted in predictable ways (Tucker et al. 2019).

We are well aware that Los Angeles, like Chicago, is distinctive for its long history and scale of its chronic gang problem. The analyses presented here based on data from Los Angeles may not generalize to other settings. Ultimately, it is in empirical matter whether retaliatory dynamics vary from one gang setting to another. The models presented here provide an opportunity to test such hypotheses in other settings.

We close with the remark that background and contagious processes estimated here do include unmeasured prevention intervention effects. The LAPD, through both traditional enforcement and the Community Safety Partnership program (Rice and Lee 2015), and the Los Angeles Mayor's Office of Gang Reduction and Youth Development (GRYD) (Tremblay et al. 2020) both respond to gang crimes with the intention to reduce the spread of violence. Therefore, the magnitude of contagious processes as measured in this paper is likely less than what would be the case in the absence of interventions. A full statistical specification of the importance of gang-related violence contagion will ultimately require controlling for these intervention effects.

Conclusions

This paper developed multivariate self-exciting point process models for comparing the characteristics of contagious violence between gang-related and non-gang contexts. Gang-related violence in Los Angeles triggers twice as many contagious offspring (e.g., retaliations) as non-gang violence, and there is little or no evidence of cross-triggering between these crime contexts. While gang-related contagious offspring are significantly more lethal than non-gang offspring, gang-related offspring are no more lethal than gang-related background crimes. Contagious gang violence is indeed different from that observed with non-gang violence. The results support intervention policies that seek to disrupt the spread of gang violence. However, since contagious offspring events represent only a fraction of all gang crimes, it is ideal target them alongside background crimes, reaping the benefits of addressing “root causes” and short-term triggers.

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Appendix

Parameter Estimation Methods

The models presented above can be estimated directly from data using current machine learning techniques. The specific method we use is a type of Maximum Likelihood Estimation (MLE) known as expectation maximization (EM). The procedures underlying the EM algorithm are very closely related to stochastic declustering (Mohler et al. 2011; Zhuang et al. 2002; Marsan and Lengline 2008). The expectation step of the EM algorithm starts with a random guess for the model parameter values. Given this guess, the probability ρ_j that event j is a retaliation caused via self-excitation, or the probability $1-\rho_j$ that it is a background event, is computed using equations analogous to Eqs. (5) and (6) in the main text. The probabilistic expectations for each event are then fed to a maximization step where a new set of parameter values (for iteration $k+1$) are determined by maximizing the likelihood with respect to the observed data. This maximization is done for all parameters taking into consideration whether crimes are labeled as gang-related or non-gang. The EM algorithm alternates between the expectation and maximization steps until there is

Table 7 Triggering parameter estimates using temporal boundary corrections of different durations

Parameter	Boundary correction in days	Estimate
k_{11}	5	0.164
k_{10}	5	1.39×10^{-3}
k_{00}	5	0.114
k_{01}	5	4.09×10^{-3}
k_{11}	10	0.164
k_{10}	10	7.13×10^{-5}
k_{00}	10	0.114
k_{01}	10	8.69×10^{-4}
k_{11}	30	0.168
k_{10}	30	1.21×10^{-4}
k_{00}	30	0.126
k_{01}	30	1.56×10^{-3}

Table 8 Parameter estimates given Monte Carlo reshuffling of gang-related and non-gang crime labels

Parameter	Shuffled estimate	Scaled parameter	Scaled estimate
$\tilde{k}_{11}$	0.037	$(1-p_1)\tilde{k}_{11}$	0.026
$\tilde{k}_{10}$	0.092	$(1-p_1)\tilde{k}_{10}$	0.028
$\tilde{k}_{00}$	0.083	$p_1\tilde{k}_{00}$	0.024
$\tilde{k}_{01}$	0.038	$p_1\tilde{k}_{01}$	0.026

no further change in the parameter values. EM is able to recover true parameter values with a high degree of certainty. Standard errors for the parameter estimates are obtained from the inverse Hessian matrix for the corresponding likelihood function (Ogata 1978). Further technical details for implementation of EM algorithms can be found in (Veen and Schoenberg 2008; Mohler 2013).

Boundary Effects

The available data is restricted to a finite temporal and spatial window. We evaluated the effect of temporal boundaries on the triggering matrix K by progressively reducing the temporal window by 5, 10 and 30 days and re-estimating the model (see Fox et al. 2016). The estimated parameters using reduced data are qualitatively the same as the full data sample (Table 7). Boundary effects are limited because the kernel support has a much shorter temporal length scale (measured in days) relative to the full data (a full year).

Null Model and Convergent-Discriminant Validity

The multivariate point process model suggests a null model for the dynamics of gang-related and non-gang crimes. Consider a hypothetical case where all violent crimes are drawn from the same random process with a common background rate μ and common triggering productivity K. Individual crimes may differ from one another in their spatial and temporal characteristics simply as a result of random variation. As a population of events, however, they are well-described by a single stochastic process. Imagine that we then randomly label a fraction p_1 of the crimes as gang-related and $1-p_1$ as non-gang. The label is independent of any measured characteristics of the crimes. If this arbitrary labeling process holds, then we expect $\left(1-p_1\right)k_{11}=p_1k_{00}$ and $\left(1-p_1\right)k_{01}=p_1k_{10}$. That is, we expect both *within-label* triggering and *between-label* cross-triggering to be equivalent after scaling by the fraction of crimes labeled as gang-related. In the special case that $p_1=0.5$, meaning that an equal number of crimes are randomly labeled as gang-related and non-gang, then the expectations is that $k_{11}=k_{00}=k_{01}=k_{10}$. Equivalence in retaliatory triggering seems unlikely given the empirical differences between gang-related and non-gang crimes in participant, situational and neighborhood characteristics (Maxson et al. 1985; Rosenfeld et al. 1999; Huebner et al. 2016). The null model is nonetheless valuable for sharpening our thinking on how to interpret parameter estimates.

The null model also suggests that the triggering pathways shown in Fig. 2 can be interpreted in a manner similar to the convergent-discriminant validity tests used by Decker and Pyrooz (2010) (see also Taylor 2015; Piquero 1999). Convergent-discriminant validity tests posit that two statistics that seek to measure the same underlying construct will be more

Table 9 Wald-Wolfowitz runs tests for randomness in time ordered labeling of crimes

Basic car	Total (N)	Gang-related (N)	Number of runs	Z	p-value
A03	217	74	90	– 1.29	0.20
A49	198	53	82	0.61	0.54
A41	190	79	89	– 0.64	0.52

strongly correlated with one another than two statistics that measure different underlying constructs. If gang-related and non-gang crime labels measure different constructs, then we would expect the *within-label* triggering to be stronger then *between-label* triggering, which is what we observe in the main model estimates. To evaluate the significance of this observation, we performed 500 Monte Carlo simulations where we shuffled the labels randomly over events and re-estimated the parameters of the multivariate model after each reshuffling. Reshuffling breaks any correlation between the labels and the underlying dynamics. Recall our null hypothesis that the estimates of k_{11} and k_{00} as well as k_{01} and k_{10} should be equivalent after sample-size scaling if the labels are no better than random. We find exactly this to be the case for the shuffled labels (Table 7). When the shuffled parameter estimates $\tilde{k}_{ij}$ are scaled using the empirical fraction $p_1 = 0.3$ of gang-related labels, the resulting scaled parameters are statistically indistinguishable (Table 8). We take this as evidence supporting a conclusion the labels correspond to different theoretical constructs with different underlying dynamics. However, this test does not test whether the theoretical constructs are biased.

Runs Tests for Biased Labeling

One potential source of bias in crime labels is a carryover effect where the classification of one crime as gang-related (or non-gang) biases the label applied to the next crime that arrives. We use the Wald–Wolfowitz runs test to assess whether labels are applied independently to each crime as it arrives, or whether they form groups suggestive of biased carryover. We examined three LAPD Basic Car areas within LAPD Patrol Divisions in the South Los Angeles study region. We assume Basic Car are exposed to crime "arrivals" from a relatively stable set of gang-related and non-gang contexts. We also assume that there is a stable set of individuals involved in labeling of crimes within a Basic Car area, allowing for potential bias to develop. The null hypothesis is that labels are applied randomly and independently from one reported crime arrival to another and that the number of runs (i.e., blocks of identically labeled crimes) should not exceed what is expected under this null hypothesis. We fail to reject the null hypothesis in each of the three Basic Car areas examined (Table 9). This suggests that crimes are labeled independently as they arrive. It also suggests that clusters of crimes generated by contagious triggering among gang-related and non-gang crimes, respectively, are not large enough to override a general pattern of random crime arrivals of each type.

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