Journal of Quantitative Criminology
https://doi.org/10.1007/s10940-024-09592-5

ORIGINAL PAPER

Measuring Online–Offline Spillover of Gang Violence Using Bivariate Hawkes Processes

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Accepted: 22 September 2024

Abstract

Objectives The goal of this research is to investigate the association between online and offline gang conflict. It does this by investigating the magnitude and causal ordering of this association with a case study of Chicago Latino gangs.

Methods Chicago Police Department records of gang shootings (N = 566) are combined with 9873 gang confrontations on social media from a Facebook page devoted to Chicago Latino gangs. A bivariate Hawkes point process is then fit to the data to estimate spillover effects from Facebook to Chicago street violence and vice versa.

Results We estimate that each shooting causes 0.068 (0.015, 0.182) negative Facebook comments directed towards the victim gang. We estimate that each negative Facebook comment directly causes 0.002 excess shootings, though this effect is not statistically significant. When focusing on the three most active gangs, the measured spillover effects are even larger. We estimate for the three most active gangs, 9% of Facebook comments are caused by shootings and 3% of shootings are caused by negative Facebook comments, however the latter effect is not statistically significant.

Conclusions The data indicates that most online negative interactions between gangs stay online. Further we find that the only causal relationship the data supports is that offline violence leads to negative interactions online. We did not find statistically significant evidence of a causal relationship in which online interactions lead to offline violence. Finally, the data suggests contextual considerations, such as the size of the gang, need to be considered when assessing such relationships.

Keywords Gangs · Social media · Gang violence · Bivariate Hawkes process

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Published online: 25 October 2024

Introduction

Advances in technology have created opportunities for street gang members to access and interact with one another in digital spaces as well as on street corners. On what Lane calls the digital street (Lane 2016), gang members can communicate aggressively with rivals 24 h a day with minimal effort. Such interactions raise the question about a negative effect of social media—whether conflict on the digital street can spill over into real world violence. On one hand, online interactions can be completely separate from the real world-gang members, for instance, might taunt or verbally joust with other groups whom they have no real world interactions, even gangs in different cities or countries. Perhaps they are mere jabs that gang members will not take seriously and thus they will not escalate (Stuart 2020). On the other hand, online interactions require far less investment of time and energy than offline interactions, and therefore may be more frequent. This greater opportunity for negative interactions could inflame gang wars and thus overall increase gang violence (Patton et al. 2017).

The predominant interest of past research is in a causal relationship in which online violence leads to offline violence (Moore and Stuart 2022; Moule et al. 2017; Patton et al. 2019; Stuart 2020). However, it is also possible that conflict begins offline and then spills over into the digital street. In such a case, gang members might share evidence of offline violence they or their compatriots have committed with the larger online audience to amplify the intimidating effects of a given incident. This is important because if online violence leads to offline violence, the reverse relationship might be an important intensifier of the dynamic, but if it does not, the impact of social media might be largely benign-or concerning in complex ways. However, data limitations have made causal relationships difficult to determine. Most of the scant research on the topic has been qualitative or theoretical in nature, and parsing out important features of the online offline gang violence nexus, including timing and magnitude, is impossible (Lane 2016; Stuart 2020; Patton et al. 2019; Lauger et al. 2020). Only one study that we are aware of has quantitatively investigated the association between online and offline gang violence. However, it focused on co-constitutive multiplex networks rather than on temporal directionality (Hsiao et al. 2023).

The current study begins to unpack the magnitude and direction of gang conflict on the digital and geographic street with two Chicago-based data sources. In addition to law enforcement reports of gang related shootings, we use data from a public Facebook page devoted to Chicago Latino gangs that includes comments and replies made in 2015 and 2016, which we match to police data for these years. We use insider gang knowledge to classify language used in comments as positive or negative towards a given gang. Two research questions drive our inquiry. First, what is the strength of the association between online and offline gang conflict? Second, what is the temporal ordering of that conflict?

As street gangs become more immersed in online conflict, assessing the online-offline relationship is an important question in contemporary studies of street gangs (for reviews see (Moore and Stuart 2022; Pyrooz et al. 2023). Online “internet banging" is a relatively new phenomenon, and it is vital that policymakers operate based on an understanding of its impact. If online conflict leads to offline violence, policies that lessen it are vital.

The outline of the paper is as follows. In Sect. 2, we review relevant literature to the present study. In Sect. 3, we provide an overview of Hawkes process models and our Bayesian estimation methodology. In Sect. 4, we describe our dataset from 2015 to 2016 that consists of shootings in Chicago where the victim is affiliated with one of thirty four Latino gangs, and negative Facebook comments that are directed towards one of the thirty four gangs. In Sect. 5, we present results from estimating the model to the data from Chicago. We estimate that each shooting (Granger) causes 0.068 (.015, 0.182) negative Facebook comments, and each Facebook comment causes 0.002 (0.000, 0.006) shootings. When focusing on the three most active gangs, these estimates increase to 0.18 (.01, 0.56) and 0.004 (0.0002, 0.01) respectively. We then discuss these results in Sect. 6.

Literature Review

The use of social media has become central in many of the daily routines of young people (Anderson and Jiang 2018). Members of gangs are no exception, and gang activity has been prevalent online for more than a decade (Décary-Hétu and Morselli 2011; Morselli and Décary-Hétu 2013; Womer and Bunker 2010). Gang activities on the digital street mimic activities in the physical street in foundational ways. Observational research of online gang behavior shows that much as they do offline, gang members on social media insult, disrespect, dare, and threaten rivals (Leverso and Hsiao 2021; Patton et al. 2013); construct violent gang identities (Lauger and Densley 2018; Pyrooz et al. 2015; Van Hellemont 2012); and promote gang culture (e.g., show off weapons) (Leverso and Hsiao 2021; Patton et al. 2013; Pyrooz et al. 2015; Morselli and Décary-Hétu 2013; Storrod and Densley 2017). In some ways the digital street is akin to a virtual graffiti wall that gangs use to represent their gang and disrespect rival gangs (Pyrooz et al. 2015; Moore and Stuart 2022).

Given the violent rhetoric online and the fact that insults readily lead to violence offline, social media interactions could theoretically inflame gang wars. Being called out or "dissed" online could have real world repercussions if it leads to offline conflict. However, social media could also defuse gang violence. If gang members view online interactions as a means of saving face and looking tough, even sufficient to avenge a slight that occurred offline, real world violence might become unnecessary. Amongst the extremely limited research, most theorizes a positive relationship between social media and gang violence. Moule et al. (2017) addressed the question by surveying 585 gang members and their unaffiliated peers and comparing their answers to the question as to whether they would commit violence in retaliation for an online insult and whether they had experienced online interactions leading to violence. In both cases, gang members were more likely to answer affirmatively. Patton et al. (2017) reported, based on a case study of a member of a Chicago gang, that her murder had been preceded by negative interactions on Twitter.

Other studies address the question by scrutinizing the conditions by which online and offline interactions are associated. General Strain theory (Agnew and White 1992; Agnew 2006) posits that strain is the underlying cause of such escalation, and Lauger and colleagues (Lauger et al. 2020) argue some online interactions but not others lead to strain. Patton et al. (2019) point out that direct threats, challenges, and disrespect designed to humiliate, when aimed at groups or people, are a subset of social media behaviors, and that these are the behaviors most likely to lead to offline violence. Stuart (2020) disputes these claims and argues that most of gang members' actions and behaviors on social media are performative, and that the primary way in which social media affects offline violence is that perpetrators learn rivals' routine activities on social media, which allows them to judge where a person they want to victimize is at a given time.

In one of the few quantitative studies on the topic Hsiao et al. (2023) investigated how networks derived from the "corner" (spatial relationships of gang territories), the "crew" (offline conflict relationships), and the "digital street" (online conflict relationships) are co-constitutive and mutually reinforce and influence each other. Using a multiplex framework and exponential graph modeling, they found correlations between the online and offline networks. However, the purpose of that study was to investigate the intertwined nature of gang interactions, not understand the causal ordering of offline and online relationships. As such time was not considered in the analysis and thus it was only a first step in empirically demonstrating causal associations. Another quantitative study was limited to audit meetings in a focused deterrence program in Philadelphia. Hyatt et al. (2021) found feuding and threatening rivals online was not correlated with offline shootings. They did find some indication that the total amount of social media use and illegal content predicted offline online gang behavior.

Nonetheless, the overall impression of the nascent research on the relationship between online interactions and offline violence is that the association is positive (Moule et al. 2017; Patton et al. 2017, 2019). Research and theory also have begun to suggest it is important to not only consider if online interactions are associated with offline violence but also the conditions that may generate this relationship (Hyatt et al. 2021; Lauger et al. 2020; Patton et al. 2019) or if practical aspects of online interactions rather than content drive their role in offline violence (Stuart 2020). In this study we focus on the time ordering absent from Hsiao et al. (2023) to illuminate if online conflict precedes and intensified the tension between the two gangs and propelled a shooting event, or if the shooting event intensifies the volume of negative interactions online.

Methods

In this paper, we investigate the extent to which negative gang interactions on Facebook are temporally associated with gang-involved shootings in Chicago. For this purpose we use bivariate Hawkes processes to model the coupled intensities of online and offline events. To perform inference, we use Bayesian estimation in STAN for simultaneously optimizing the likelihood to find optimal parameters, and for providing estimates of the uncertainty of the model parameters. In this section we provide the details of our modeling approach.

Point Processes

A point process is a probabilistic model for the occurence of sets of points on a space X, often assumed to be a subset of $\mathbb{R}^d$, where d is the space dimension. Oftentimes, point processes describe the occurrence over time of random events in which the occurrence times t_i's are revealed one by one as time evolves. This can be presented as

$$\{t_1, t_2, \ldots, t_d\} \text{ , such that } t_1 < t_2 < t_3 < \ldots t_{d-1} < t_d. \tag{1}$$

The collection of event times up to time t, $H_t = \{t_i | t_i < t\}$, is called the history of the process.

Let N_t be a random function defined on time $t \geq 0$ that takes integer values and is uniquely determined by the above sequence of event times t_i. In other words, N_t is a function that counts the number of events up to time t:

$$N_t = \sum_{i \geq 1} \mathbb{1}_{\{t \geq t_i\}}, \tag{2}$$

where $\mathbb{1}$ is the indicator function that takes value 1 when $t \geq t_i$ and 0 otherwise. The function N_t takes jumps of size 1 at each event time t_i, and initially $N_0 = 0$. Therefore, the set of event times $\{t_1, t_2 \ldots\}$ and the corresponding counting process, N_t, are an equivalent presentation of the underlying point process (Rizoiu et al. 2017).

A point process can also be characterized by its conditional intensity,

$$\lambda(t) = \lim_{\Delta t \to 0} E[N[t, t + \Delta t) | H_t] / \Delta t, \tag{3}$$

which can be interpreted as the rate of events per unit time, conditioned on the history of the process. A well-known example of a point process is the Poisson process, which is characterized by its conditional intensity $\lambda(t) = \lambda$ given by a constant.

Univariate Hawkes Processes

A Hawkes process is a type of point process that models self excitement between event times (Hawkes 1971; Rizoiu et al. 2017), where the occurrence of an event increases the intensity of events in the near future. In the present work, we use Hawkes processes to model the change in intensity of shootings when a gang member posts on Facebook a negative comment about a rival gang (online activity), or the change in the intensity of such Facebook comments after a shooting event. A bivariate Hawkes process is used in the situation where there are two types of events (see Fig. 1), and cross-excitation is possible between the event types. The model allows us to measure temporal associations between events in the form of Granger causality (Xu et al. 2016).

In the univariate case (single event type), the Hawkes process intensity function is given by,

$$\lambda(t) = \mu + \sum_{t_i < t} \phi(t - t_i), \tag{4}$$

where μ characterizes the "baseline" (or "background") Poisson rate of events (that occur at random), and $\phi(t - t_i)$, called the triggering kernel, models the increase in the intensity after the occurrence of event i at time t_i. The kernel ϕ is a function of the delay $t - t_i$ between the current time and the timestamp of the previous event. It is worth noting that ϕ satisfies:

$$\phi(x) \geq 0, \text{ for, } \forall x \in \mathbb{R}^+ \tag{5}$$

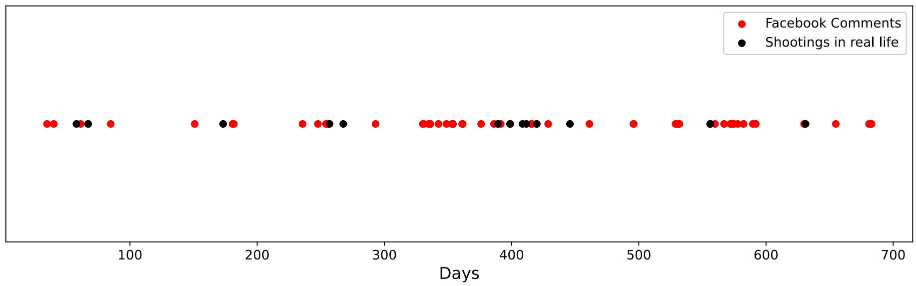

Fig. 1 2015–2016 times of occurrences of Facebook comments and shootings where the victim is affiliated with the Ambrose gang in Chicago

$$\phi(x) = 0, \ \forall x < 0. \tag{6}$$

The first property assures that ϕ is a non-negative function, while the second one underlines the fact that ϕ models the causal relationship between an event in the past and the intensity in the future. In the present work we use the exponential kernel, $\phi(t - t_i) = \alpha\beta e^{-\beta(t-t_i)}$.

In the context of gang violence, the baseline rate μ can be viewed as the rate of initial random events that might spark an outbreak of violence. On the other hand, the parameter α, called the reproduction number in epidemiology and productivity parameter in seismology, defines the expected number of new events directly caused by a previous event. The parameter β determines the serial interval between causally connected events and is equivalent to the recovery rate in a SIR model (Rizoiu et al. 2018). The density $\beta e^{-\beta(t-t_i)}$ models the probability distribution of delays between parent–child events that are causally connected. An example intensity from a simulation of a univariate Hawkes process is illustrated in Fig. 2.

Use of Hawkes Processes in Criminology

Hawkes processes have been used to model near-repeat event patterns in burglary and robbery data in Los Angeles (Mohler et al. 2011), gun violence in Chicago (Mohler 2014), and gang rivalry networks in Los Angeles (Egesdal et al. 2010). Hawkes processes have also been used in the allocation and assessment of police interventions (Mohler et al. 2015; Park et al. 2021). In comparison with spatial regression models that require discretizing time and space, point processes are continuous time (and space) models for the occurence of events. However, as with regression models, point process models can also incorporate spatial covariates (Reinhart and Greenhouse 2018; Mohler et al. 2018). For a review of self-exciting point processes see (Reinhart 2018).

Multivariate Hawkes Processes

Assume now that our observed data consists of event times at one of D nodes in a network. In this case the event times at node i can be denoted as $y_i = (t^i_1, \ldots, t^i_{N_i})$, where N_i is the number of events at node i. Such data can be modeled with a multivariate Hawkes

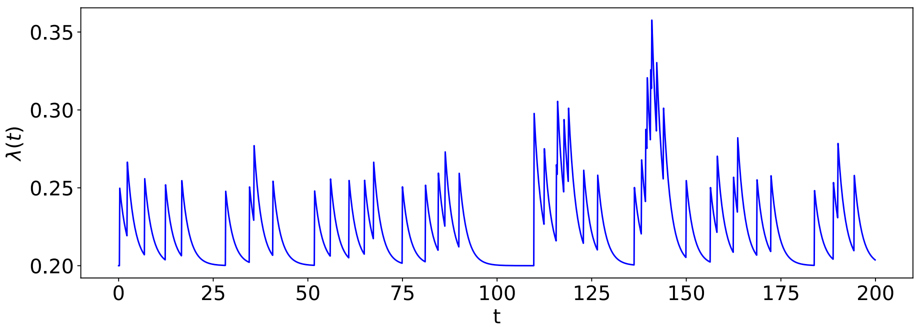

Fig. 2 Plot of the conditional intensity of a univariate Hawkes process using synthetic data with decay parameter $\beta = 0.5$, baseline intensity $\mu = 0.2$ and reproduction parameter $\alpha = 0.1$

process, where the conditional intensity for a multivariate (D-dimensional) Hawkes process is given by Deutsch and Ross (2022),

$$\lambda_i(t) = \mu_i + \sum_{j=1}^{D} \sum_{k:t>t_k^j}^{N^j} \phi_{i,j}(t - t_k^j). \tag{7}$$

Here μ_i is the baseline intensity of node i (assumed stationary Poisson), and the kernel $\phi_{i,j}(t)$ models cross-excitation from node j to node i. We assume the kernel takes the form,

$$\phi_{i,j}(t) = \alpha_{i,j}\beta_{i,j}exp(-\beta_{i,j}t)\mathbb{1}_{t>0}, \tag{8}$$

where $\mathbb{1}$ is the indicator function that takes 0 when $t \leq 0$ and 1 otherwise. In the multivariate setting, α is interpreted as a reproduction matrix, and its element α_{ij} is the expected number of events of type i triggered by an event of type j. Similar to the univariate case, β_{ij} determines the decay rate of cross-excitation from node j to node i.

In this work we focus on a bi-variate Hawkes process model for each gang (indexed by g). In this model there are two nodes for a gang, one representing negative Facebook comments directed toward the gang by other gangs, and the other node representing shootings where the victim is from that gang. In particular, the baseline rates of online and offline attacks are given by $\mu_g = [\mu_1^{\mathrm{g}}, \mu_2^{\mathrm{g}}]$, while the reproduction and the decay matrices have the form,

$$\alpha = \begin{pmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{pmatrix} \tag{9}$$

$$\beta = \begin{pmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22}. \end{pmatrix} \tag{10}$$

Here negative Facebook interactions (comments) are indexed by 1 and shootings are indexed by 2. The parameter α_{12} then represents the averaged number of negative Facebook interactions (Granger) caused by shootings, whereas α_{21} represents the average number of shootings caused by negative Facebook interactions directed towards that same gang. We let the reproduction and decay parameter matrices be shared across gangs in our data (to reduce variance in parameter estimates given the size of the data for each gang), whereas we allow the baseline rates to vary across gangs. The equation for the conditional intensity is then given by,

$$\lambda_1^{\mathrm{g}} = \mu_1^{\mathrm{g}} + \sum_{k:t>t_k^1}^{N_{\mathrm{g}}^1} \alpha_{11}\beta_{11}e^{-\beta_{11}(t-t_k^1)} + \sum_{k:t>t_k^2}^{N_{\mathrm{g}}^2} \alpha_{12}\beta_{12}e^{-\beta_{12}(t-t_k^2)} \tag{11}$$

$$\lambda_2^{\mathrm{g}} = \mu_2^{\mathrm{g}} + \sum_{k:t>t_k^1}^{N_{\mathrm{g}}^1} \alpha_{21}\beta_{21}e^{-\beta_{21}(t-t_k^1)} + \sum_{k:t>t_k^2}^{N_{\mathrm{g}}^2} \alpha_{22}\beta_{22}e^{-\beta_{22}(t-t_k^2)}, \tag{12}$$

where $(N_{\mathrm{g}}^1, N_{\mathrm{g}}^2)$ are the number of events online (Facebook) and offline (shootings) of a specific gang respectively.

We plot the conditional intensities from a simulated bi-variate (2D) Hawkes process in Fig. 3. The regions of high and low event activity are correlated across the two processes due to cross-excitation from one to the other.

Hawkes Process Likelihood and Estimation with Stan

Given observed event data, and a specified Hawkes process model, inference upon unknown parameters is required. This can be achieved by maximizing the likelihood (Bonnet et al. 2021), or through a Bayesian approach by sampling from a posterior distribution given priors on the model parameters. Given the Hawkes process conditional intensity $\lambda_\theta(t)$ that depends on unknown parameters θ, the log-likelihood function L_t with respect to the observations $T_1, \dots, T_{N(t)}$ is given by:

$$L_t(\theta) = \sum_{k=1}^{N(t)} \log(\lambda_\theta(T_k)) - \int_0^t \lambda(s)ds. \tag{13}$$

We use the probabilistic programming language Stan to evaluate the log-likelihood function (13) and estimate the parameters μ_i, α_{kj} and β_{kj}. Stan provides full Bayesian inference for continuous-variable models through Markov chain Monte Carlo optimization (Carpenter et al. 2017).

To evaluate the log-likelihood function defined in expression (13), the integral $\int_0^t \lambda(s)ds$ must be analytically determined or approximated. We employ the following approximation using facilitated estimation (Schoenberg 2013) (assuming T, the length of the observation window, is large compared to the longest time scale of the decay rate matrix β):

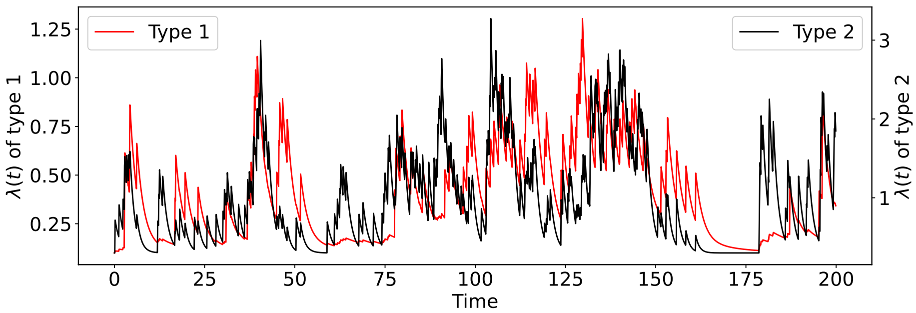

Fig. 3 Example of a bi-variate Hawkes process in which we generated synthetic data that corresponds to the occurrences of events marked 1 or 2. The reproduction matrix used is $\alpha = \begin{pmatrix} 0.5 & 0.1 \\ 0.2 & 0.6 \end{pmatrix}$, and the decay matrix is $\beta = \begin{pmatrix} 0.5 & 0.1 \\ 1 & 0.7 \end{pmatrix}$, while the background rate was set to $\mu = [0.1, 0.3]$

$$
\begin{aligned}
L(\theta) = \sum_{\mathrm{g}} \Bigg[& \sum_{k=1}^{N_{\mathrm{g}}^1} \log\left(\lambda_1(t_k^1)\right) + \sum_{k=1}^{N_{\mathrm{g}}^2} \log\left(\lambda_2(t_k^2)\right) - \int_0^T \mu_1^{\mathrm{g}} ds - \int_0^T \mu_2^{\mathrm{g}} ds \\
& - \sum_{k:t>t_k^1}^{N_{\mathrm{g}}^1} \alpha_{11}\beta_{11} \int_{t_k^1}^T e^{-\beta_{11}(s-t_k^1)} ds - \sum_{k:t>t_k^2}^{N_{\mathrm{g}}^2} \alpha_{12}\beta_{12} \int_{t_k^2}^T e^{-\beta_{12}(s-t_k^2)} ds \\
& - \sum_{k:t>t_k^1}^{N_{\mathrm{g}}^1} \alpha_{21}\beta_{21} \int_{t_k^1}^T e^{-\beta_{21}(s-t_k^1)} ds - \sum_{k:t>t_k^2}^{N_{\mathrm{g}}^2} \alpha_{22}\beta_{22} \int_{t_k^2}^T e^{-\beta_{22}(s-t_k^2)} ds \Bigg]
\end{aligned}
\tag{14}
$$

$$
\begin{aligned}
L(\theta) = \sum_{\mathrm{g}} \Bigg[& \sum_{k=1}^{N_{\mathrm{g}}^1} \log\left(\lambda_1(t_k^1)\right) + \sum_{k=1}^{N_{\mathrm{g}}^2} \log\left(\lambda_2(t_k^2)\right) - \mu_1^{\mathrm{g}} T - \mu_2^{\mathrm{g}} T \\
& + \sum_{k:t>t_k^1}^{N_{\mathrm{g}}^1} \alpha_{11}\beta_{11} \frac{1}{\beta_{11}} \left[e^{-\beta_{11}(s-t_k^1)}\right]_{t_k^1}^T + \sum_{k:t>t_k^2}^{N_{\mathrm{g}}^2} \alpha_{12}\beta_{12} \frac{1}{\beta_{12}} \left[e^{-\beta_{12}(s-t_k^2)}\right]_{t_k^2}^T \\
& + \sum_{k:t>t_k^1}^{N_{\mathrm{g}}^1} \alpha_{21}\beta_{21} \frac{1}{\beta_{21}} \left[e^{-\beta_{21}(s-t_k^1)}\right]_{t_k^1}^T + \sum_{k:t>t_k^2}^{N_{\mathrm{g}}^2} \alpha_{22}\beta_{22} \frac{1}{\beta_{22}} \left[e^{-\beta_{22}(s-t_k^2)}\right]_{t_k^2}^T \Bigg]
\end{aligned}
$$

Thus the log-likelihood function can be approximated as,

$$
\begin{aligned}
L(\theta) \simeq \sum_{\mathrm{g}} \Bigg[& \sum_{k=1}^{N_{\mathrm{g}}^1} \log\left(\lambda_1(t_k^1)\right) + \sum_{k=1}^{N_{\mathrm{g}}^2} \log\left(\lambda_2(t_k^2)\right) - \mu_1^{\mathrm{g}} T - \mu_2^{\mathrm{g}} T \\
& - \left(\alpha_{11} + \alpha_{21}\right) N_{\mathrm{g}}^1 - \left(\alpha_{22} + \alpha_{12}\right) N_{\mathrm{g}}^2 \Bigg]
\end{aligned}
\tag{15}
$$

In Stan we perform Hamiltonian Monte Carlo with 1000 samples. For the prior densities we use,

$$
\begin{aligned}
& \alpha_{11} \sim beta(1,1)\ ,\ \alpha_{12} \sim beta(1,1)\ ,\ \alpha_{21} \sim beta(1,1)\ ,\ \alpha_{22} \sim beta(1,1) \\
& \beta_{11} \sim cauchy(0,5)\ ,\ \beta_{12} \sim cauchy(0,5)\ ,\ \beta_{21} \sim cauchy(0,5)\ ,\ \beta_{22} \sim cauchy(0,5) \\
& \mu_1^{\mathrm{g}} \sim cauchy(0,5)\ ,\ \mu_1^{\mathrm{g}} \sim cauchy(0,5).
\end{aligned}
\tag{16}
$$

The choice of the distributions in Eq. (16) is motivated by the fact that we initially do not have much information about the parameters. Therefore, we use an uninformative Cauchy distribution with a large variance.[1] On the other hand, for the Hawkes process to be well-posed, the reproduction matrix α_{ij} is restricted to having elements in [0, 1] using a uniform prior.

[1] We verify that the priors are sufficiently uninformative by setting the priors to *cauchy*(0, 10) to estimate the parameters, and then checking that the resulting parameter estimates are close to those when using *cauchy*(0, 5).

Data

To analyze the association and temporal ordering of online and offline gang conflict, this study uses Chicago Latino gangs as a case study over a 23-month period (January 2015 until November 2016) and two data sources: a novel data set pertaining to gang interactions on a public Facebook page devoted to Chicago Latino gangs and data on violent, gang-involved events from Chicago Police Department (CPD) records.

The period examined here is one in which most gang violence is intra-racial. This reflects long-term trends in Chicagoland gang violence, as reflected in historical data and recent studies. For example, research by Papachristos (2009) and subsequent studies (Papachristos et al. 2013) have found that over 95% of gang violence was intra-racial during the periods 1994–2000 and 2005–2009. This pattern persists in the current time period and is reflected in our data as well.

In contrast, patterns of violence reflect a significant shift in that there are no longer structured alliances between gangs. Historically Chicago gangs were part of one of two alliances in the city known as “The Folks” and “The People.” The vast majority of gang violence involved members of a gang in the Folks attacking members of a gang in the People or vice versa (Conquergood 1993; Hagedorn 2020; Papachristos 2009). Since the breakdown of the alliance system, “everybody killer” stance prevails among the city’s gangs (Aspholm 2019; Leverso 2020; Stuart 2020). The result is a shift towards more sporadic, haphazard, and less territorially focused gang violence.

Taken together our study of gang violence and social media interactions, among Latino gangs, occurs against this backdrop of no or very few alliances (i.e., gangs are “everybody killer”) and prevalent intra-racial conflicts. The fragmented nature of these gangs and their sporadic confrontations on social media highlight a new dynamic in gang violence. In the discussion section of our study, we further explore these themes and their implications for understanding the current landscape of gang-related violence in Chicago, focusing on the Latino gang community.

To understand gang culture and communication we draw on the lived experience of the lead author. The lead author was gang involved in a Chicago Latino gang in the late 1990 s and thus has the knowledge to interpret the language in the Facebook data. He also assembled a team of former gang members through personal connections to assist in this task. Chicago is the home turf of a significant number of Latino gangs and thus provides a useful context for the research. Facebook data were gathered in 2015–2016, as members of the population of interest were commenting actively on public Facebook pages during that time period.

The public Facebook page we study does not have moderation, but it has an unidentified administrator to whom posters must send material that then appears on the page. Common posts include performances of gang identity-including disrespecting rival gangs-and images in which gang members brandish weapons. The former include images of people, presumably gang members, “throwing up” gang signs, that is, doing them in the standard way, and “throwing down” rival signs-performing them upside down. Such images are the most common in our data set. Gang graffiti, either photographs or digital images, is the second most common type of post. Much like gang signs, gang graffiti can be displayed positively through positive references to the gang’s name and symbol, or negatively through a disrespectful use or distortion of a rival gang’s name and symbol. Frequently attachments to the gang name-“love” for positive references, “killer” or “k” for negative references-indicate the slant. For example, “two six killer” indicates one who kills members of Gangster Two

Six gang and is a phrase of disrespect towards members of that gang. Photographs may be taken in a gang's territory or, more provocatively, in that of its rivals, and images include computer-generated memes as well as scans of hand-drawn graphics. Occasionally posts feature the name or picture of a dead rival followed by "burns" or "rotz," meaning they are "burning" or "rotting in the ground". The lead author's experience suggests that while gang signs posts and gang graffiti are roughly equal in their level of disrespect to rivals, such insults to the dead are far more inflammatory than other posts.

Comments, unlike posts, appear instantly. The page was set such that any visitor can post a comment. Interactions are generally hostile, in line with contemporary Chicago gang culture, in which there are no inter-gang alliances. The same types of material that appear in posts appear in comments, but questions such as "Who is that?" and ridicule are also common. Typically the comments consist of a back-and-forth in which individuals mock each other or the material posted.

We operationalized positive and negative terms from comments posted on the Facebook page based on a dictionary with terms assembled by the team of former gang members along with the lead author. It includes universal suffixes such as "love" "rotz" and "k"; gang-specific keywords; and those generated from exploratory investigations of the data. Table 1 highlights this using the example of Gangster Two Six. The first row, universal suffixes, can be used to represent membership in or disrespect towards any gang. Positive suffixes include words like love, luv, and crazy. Acronyms are also used with the letter "N." For example "TSN" denotes Two Six Nation and "gtsn" denotes Gangster Two Six Nation. The next row, gang-specific keywords, includes phrases only associated with a given gang. In this example Amor De Conejo is a common phrase used only by members of Gangster Two Six, a reference to their symbol, the rabbit. The iii signifies three dots, another symbol of the Gangster Two Six. Negative gang-specific terms for Gangster Two Six include "two shit" and the demasculinizing "bitch ass bunnies." Dorkside is a derogatory statement based on one of the focal territories of the Two Six which they call the Darkside.

Finally the third row includes words that were added by exploratory searches of the data. Often words added here were based on variant spellings of "twosixlove," less common usages "26 for life" or specific locations. For example "kktown two six" is a reference to the Gangster Two Six turf in "K town" (a section of Chicago where all the streets begin with the letter K). The double k in the spelling of K town suggests that Gangster Two Six are [Latin] Kings killers. Coding algorithms were developed to code all the comments as positive or negative for all the gangs in the study, conditional on whether they included any phrases from the dictionary. For this study we investigate whether online

Table 1 Example dictionary coding for gangster two six

	Positive words	Negative words
Universal suffixes	Two six love, two six luv, Two six nation, Two six crazy, Two six worlk gtsn	Two six killer, tsk, gtsk
Gang-specific keywords	Amor de conejo, iii, dos seis	Two shit, dorkside, bitch as bunnies
Exploratory data analysis	Kktown twosix, twosixlove, 26 for life	Ghot, two-shit, twok shit, 26 k

hostility operationalized by negative comments from the dictionary correlates with offline gun violence; the positive dictionary was not formally used in the analysis. As we have documented elsewhere, gang members often know the affiliations of the commenters they interact with on the Facebook page. Therefore, when someone makes positive or negative statements about a gang, it is assumed that they are aware of the affiliations they are discussing.

Data on offline gang violence are derived from police records obtained from a freedom of information request. The police records dataset includes all recorded fatal and non-fatal shooting events (with a label for the victim's gang affiliation) during the study period, which were then filtered to focus on gang-related shootings based on victims' gang affiliations. It covers 34 gangs, with sample sizes detailed in Table 2.

While the use of police data raises concerns regarding biases and measurement errors, we have reason to believe the dataset is sufficiently accurate to support our aims. Decker and Pyrooz (2010) found that police reports on gang homicide across major U.S. cities exhibit high internal reliability and considerable external validity. In fact, Katz et al. (2000) demonstrated that the accuracy of police-reported gang measures is particularly high in cities that have specialized gang-focused policing units, which Chicago does. We follow (Papachristos 2009; Papachristos et al. 2013) and Hsiao et al. (2023) in using Chicago police data in this paper.

Results

We fit the bi-variate Hawkes process given by Eq. (7) to the Chicago data on negative Facebook comments and shootings. As outlined in Sect. 3, the matrix parameters α and β are shared across gangs, whereas the baseline rates are estimated for each gang. We report the posterior mean and 95% confidence intervals for α and β in Table 3 and for the baseline rates in Table 4.

In Table 3, we observe that $\alpha_{11} = 0.603$, which is the estimated number of additional negative Facebook comments directly caused by each initial comment. We estimate that $\alpha_{22} = 0.031$, which is the number of additional shootings directly caused by a previous shooting. On average, we estimate that $\alpha_{12} = 0.068$ negative Facebook comments are caused by each shooting event and $\alpha_{21} = 0.002$ shootings are caused by each negative Facebook comment. We note that the lower end of the 95% confidence interval for α_{21} is close to zero, therefore based on our analysis we find that spillover effects from Facebook to offline violence are not statistically significant. The timescale parameter matrix β is in units of days^{-1}, and thus the time scale of contagion effects is estimated to be on the order of 8 h to 1 day. We also plot the conditional intensities of the estimated model for three example gangs (AMBRO, ASR, and BISHOP) in Fig. 4. See the "Appendix" for additional plots of the estimated intensities for all other gangs, along with the gang name abbreviation key.

Given that the Hawkes process is an infinite branching process, we have that the expected number of events per unit time $\bar{n}_{\text{Shooting}}$ and $\bar{n}_{\text{Facebook}}$ satisfies,

$$\begin{pmatrix} \bar{n}_{\text{Facebook}} \\ \bar{n}_{\text{Shooting}} \end{pmatrix} = \sum_{k=0}^{\infty} \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{21} \end{pmatrix}^{k} \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} = (I - \alpha)^{-1} \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}. \tag{17}$$

Letting $\bar{n}^{0}_{\text{Facebook}}$ be the expected number of Facebook comments when $\alpha_{12} = 0$ (e.g. there is no contribution of shootings), we can then use Eq. 17 to estimate the percentage of

Table 2 Sample sizes for online and offline events for all gangs

Gang	Shootings sample size	Facebook comments sample size
AMBRO	15	63
ASR	6	189
BISHOP	7	69
COBRA	32	208
COUNTS	5	56
DEUCE	4	169
DRAGON	9	37
EAGLES	5	94
FSTONE	7	69
GENT	3	47
IMP_GANG	11	247
INSANEPOPE	1	7
JIVERS	6	15
KGB	4	13
LDRAGON	1	1
LK	144	5071
LOVERS	3	38
MKS	9	178
MLD	48	765
OAS	5	98
PACHUCO	4	21
PPS	2	9
RAZA	26	115
S4CH	5	4
SAINT	26	190
SD	74	981
SGD	11	447
SLORDS	3	26
STYLER	1	45
SVL	2	28
TS	81	425
TWOTWOBOY	2	35
VIK	1	90
YLOC	3	23

Table 3 The mean and 95% confidence interval for the reproduction and the decay matrices for all gangs

Matrix element	Mean	95% confidence interval (CI)
α_{11}	0.603	[0.588, 0.62]
α_{12}	0.068	[0.015, 0.182]
α_{21}	0.002	[0.0001, 0.006]
α_{22}	0.031	[0.003, 0.09]
β_{11}	2.995	[2.988, 2.999]
β_{12}	1.673	[0.088, 2.919]
β_{21}	0.839	[0.062, 2.593]
β_{22}	0.956	[0.079, 2.606]

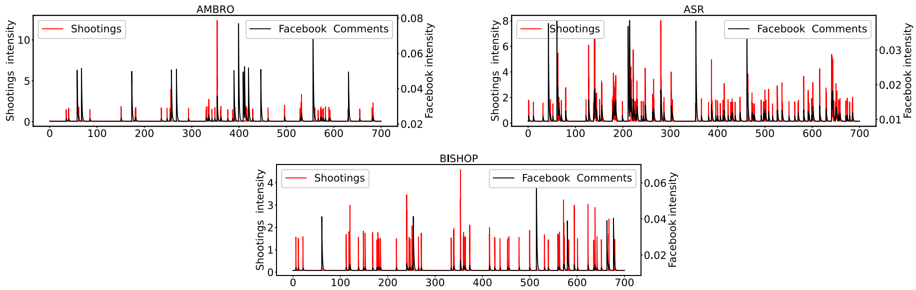

Fig. 4 The estimated conditional intensities of AMBRO, ASR and BISHOP gangs with respect to time (in days)

Facebook comments attributed to shootings and, similarly, the percentage of shootings attributed to Facebook comments:

$$\begin{aligned} \%\text{Shootings} \rightarrow \text{FB} &= 100\left(1 - \frac{\bar{n}^0_{\text{Facebook}}}{\bar{n}_{\text{Facebook}}}\right) \\ \%\text{FB} \rightarrow \text{Shootings} &= 100\left(1 - \frac{\bar{n}^0_{\text{Shootings}}}{\bar{n}_{\text{Shootings}}}\right). \end{aligned} \tag{18}$$

In Table 5 we display the percentage of events attributed to cross-excitation disaggregated by each individual gang.

Fitting the Model to the Three Most Active Gangs

To separate out potential differences between larger and smaller gangs, we next fit the model to the three most active gangs: LATIN KINGS (LK), SATAN DISCIPLES (SD) and TWO SIX (TS). We again estimate the reproduction and decay matrices (shared across these three gangs), along with the background intensities for each of the three gangs (which are allowed to vary across gangs). These results are shown in Tables 6 and 7 (and we plot estimated conditional intensities in Fig. 5). Here we have consistent patterns in terms of the time scale of excitation, and in terms of offline to online excitation being greater than online to offline excitation. However, we do observe that self-excitation and

Table 4 Estimated background rates for online and offline activities as well as their respective 95% confidence interval when considering all gangs

Gang	Facebook comment baseline intensity	Facebook comment baseline intensity 95% CI	Shootings baseline intensity	Shootings baseline intensity 95% CI
AMBRO	0.060	[0.045, 0.077]	0.022	[0.013, 0.032]
ASR	0.138	[0.113, 0.165]	0.009	[0.004, 0.016]
BISHOP	0.075	[0.059, 0.093]	0.011	[0.006, 0.019]
COBRA	0.165	[0.138, 0.194]	0.045	[0.033, 0.060]
COUNTS	0.055	[0.041, 0.071]	0.008	[0.003, 0.014]
DEUCE	0.145	[0.122, 0.171]	0.007	[0.003, 0.013]
DRAGON	0.036	[0.026, 0.048]	0.014	[0.007, 0.022]
EAGLES	0.080	[0.061, 0.101]	0.008	[0.003, 0.015]
FSTONE	0.054	[0.039, 0.071]	0.011	[0.005, 0.019]
GENT	0.032	[0.022, 0.044]	0.006	[0.002, 0.011]
IMP_GANG	0.195	[0.166, 0.227]	0.016	[0.009, 0.025]
INSANEPOPE	0.010	[0.005, 0.017]	0.003	[0.000, 0.006]
JIVERS	0.017	[0.010, 0.025]	0.010	[0.005, 0.017]
KGB	0.014	[0.008, 0.022]	0.007	[0.003, 0.013]
LDRAGON	0.003	[0.000, 0.007]	0.003	[0.000, 0.007]
LK	2.120	[1.974, 2.269]	0.185	[0.142, 0.220]
LOVERS	0.031	[0.021, 0.043]	0.006	[0.002, 0.011]
MKS	0.110	[0.087, 0.133]	0.014	[0.007, 0.022]
MLD	0.482	[0.432, 0.534]	0.066	[0.049, 0.083]
OAS	0.083	[0.065, 0.103]	0.008	[0.003, 0.014]
PACHUCO	0.020	[0.012, 0.030]	0.007	[0.003, 0.013]
PPS	0.014	[0.007, 0.022]	0.004	[0.001, 0.009]
RAZA	0.090	[0.069, 0.112]	0.038	[0.026, 0.050]
S4CH	0.007	[0.003, 0.013]	0.008	[0.004, 0.015]
SAINT	0.146	[0.119, 0.173]	0.037	[0.025, 0.050]
SD	0.556	[0.497, 0.612]	0.101	[0.081, 0.122]
SGD	0.343	[0.303, 0.385]	0.016	[0.008, 0.025]
SLORDS	0.027	[0.017, 0.039]	0.006	[0.002, 0.011]
STYLER	0.045	[0.033, 0.060]	0.003	[0.000, 0.007]
SVL	0.021	[0.012, 0.031]	0.004	[0.001, 0.008]
TS	0.273	[0.234, 0.311]	0.113	[0.090, 0.136]
TWOTWOBOY	0.036	[0.025, 0.050]	0.004	[0.001, 0.009]
VIK	0.078	[0.061, 0.095]	0.003	[0.001, 0.007]
YLOC	0.024	[0.015, 0.035]	0.006	[0.002, 0.010]

cross-excitation play a greater role amongst the top three gangs in comparison to when all 34 gangs are aggregated together. For example, the offline to online excitation parameter α_{12} increases from 0.068 to 0.18 when isolating the top three gangs. Similarly, the online to offline excitation parameter estimate increases from 0.002 to 0.004.

Table 5 Percentage of Facebook comments attributed to shootings (middle column) and percentage of shootings attributed to Facebook comment cross-excitation (right column)

Gang	%Shootings $\rightarrow$ FB	%FB $\rightarrow$ Shootings
AMBRO	1.383	2.485
ASR	6.687	0.514
BISHOP	3.139	1.094
COBRA	1.794	1.915
COUNTS	3.405	1.009
DEUCE	9.393	0.366
DRAGON	1.299	2.645
EAGLES	4.537	0.757
FSTONE	2.342	1.467
GENT	2.782	1.235
IMP_GANG	5.569	0.617
INSANEPOPE	1.744	1.970
JIVERS	0.865	3.974
KGB	1.033	3.327
LDRAGON	0.523	6.566
LK	5.360	0.641
LOVERS	2.647	1.298
MKS	3.787	0.907
MLD	3.507	0.980
OAS	5.103	0.673
PACHUCO	1.396	2.462
PPS	1.599	2.149
RAZA	1.199	2.865
S4CH	0.449	7.653
SAINT	1.932	1.779
SD	2.655	1.294
SGD	9.778	0.351
SLORDS	2.256	1.523
STYLER	7.132	0.482
SVL	2.649	1.297
TS	1.207	2.845
TWOTWOBOY	3.967	0.866
VIK	11.708	0.293
YLOC	2.130	1.613
Aggregate	3.318	1.036

We also note that the percentage of events attributable to cross-excitation is higher when focusing on the top three gangs. In Table 8, we observe that for LK, 13.08% of shootings are attributed to Facebook comments, compared to an estimate of 5.36% when all 34 gangs are estimated together. Similar increases are observed for SD (increase from 2.655 to 7.694%) and TS (increase from 1.207 to 3.804%). Offline to online excitation also increases when isolating the top three gangs, where the percentage of Facebook

Table 6 The mean and 95% confidence interval for the reproduction and the decay matrices for the top three gangs

Matrix element	Mean	95% confidence interval(CI)
α_{11}	0.747	[0.725, 0.769]
α_{12}	0.18	[0.01, 0.559]
α_{21}	0.004	[0.0002, 0.01]
α_{22}	0.074	[0.011, 0.208]
β_{11}	2.995	[2.984, 2.999]
β_{12}	0.984	[0.078, 2.721]
β_{21}	0.807	[0.078, 2.581]
β_{22}	1.01	[0.061, 2.662]

Table 7 Estimated background rates and their respective 95% CI for online and offline events associated with the top three gangs (excluding all the other gangs)

Gang	Facebook comments baseline intensity	Facebook comments baseline intensity 95% CI	Shootings baseline intensity	Shootings baseline intensity 95% CI
LK	1.534	[1.371, 1.691]	0.164	[0.110, 0.210]
SD	0.489	[0.427, 0.548]	0.096	[0.073, 0.118]
TS	0.247	[0.197, 0.295]	0.106	[0.083, 0.130]

Table 8 The percentage of events of each type estimated to be (Granger) caused by events of the other type, when considering only the top three gangs

Gang	%Shootings $\rightarrow$ FB	%FB $\rightarrow$ shootings
LK	13.085	2.329
SD	7.694	3.960
TS	3.804	8.009
Aggregate	9.145	3.332

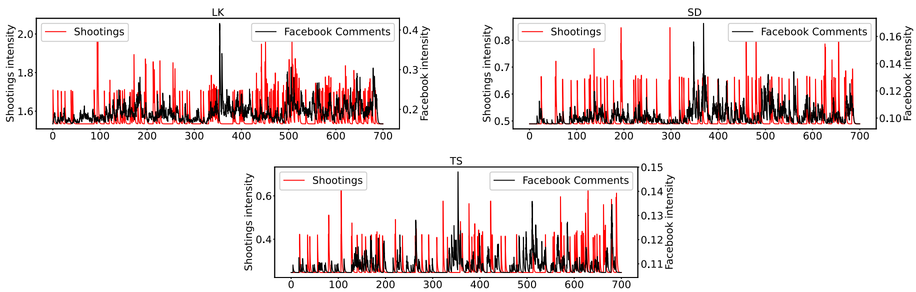

Fig. 5 Plots of the conditional intensities with respect to time (in days) associated with the top three gangs LK, SD and TS when treated alone

comments attributed to shootings increases from 0.641 to 2.329% (LK), 1.294 to 3.96% (SD) and 2.845 to 8.009% (TS).

Discussion

Understanding the gang violence-social media link is an important question in contemporary gang research. Some scholars have called social media a vector for youth violence (Patton et al. 2014). Others theorize that this is an overstatement Stuart (2020). However, such statements have been derived mostly from literature reviews or small qualitative samples. To begin to address the resulting gap, this study used Latino gangs in Chicago as a case study and investigated the strength and direction of negative interactions online to offline victimization. With these data we use a bivariate Hawkes point process to estimate the probability that a negative Facebook comment leads to a gang-involved shooting and vice versa. We draw four conclusions.

First we observed that online fighting mostly stays online. We estimate that the majority of negative interactions online are caused by previous online altercations (this effect is even larger when we subset on the top three gangs). In addition, as shown in Table 2, there are many more negative online interactions in the data than offline victimizations. Clearly from this observation, if spillover occurs from the digital street, it is not frequent or typical. Thus future research should continue to investigate the conditions that lead to spillover.

Our second conclusion is that we found limited statistical evidence that online conflict spills over into offline conflict. The reproduction number of shootings caused by Facebook comments was estimated to be between.0001 and.006 (all gangs) and between.0002 and.01 for the 3 most active gangs (i.e., the left end of 95% confidence intervals of the online to offline reproduction number are close to zero). Thus with these data we cannot state that online interactions cause offline violence. This suggests the causal link between online interactions and offline link is potentially over stated, if it exists, but future research should explore the topic further.

Our analysis did find evidence that offline violence caused online conflict. This result suggests that gang members take to social media after a violent confrontation, presumably to brag about the events and use them to gain status over other gangs. This finding is consistent with previous research that found, via content and qualitative analysis, that gang members use social media to brag about events and appear dominant over rivals (Hsiao et al. 2023; Stuart 2020; Lauger and Densley 2018; Lane 2016). While scholars have rightly focused on violence as the outcome in associations between online interactions and offline violence, the results of this study are nonetheless concerning. For example, a focal means of status attainment within a gang is acting tough, fearless, and not backing down from fights (Fagan and Wilkinson 1998; Short and Strodtbeck 1965; Thrasher 2013), and having an audience is important to such performances Hughes and Short Jr (2005). If a member of a gang does something worthy of status, social media then increases the size of the audience. Thus social media may increase gang violence by providing a wider mechanism for gaining status. Future research should further untangle how online interactions may impact offline violence in complex ways.

Finally, we found that the strength of the association between online and offline conflict is stronger for the three largest Latino gangs in the Chicago area. This applies to both the overall significant causal relationship in one direction and the insignificant relationship in the other. Almost 100 years ago, Thrasher came to the conclusion that no two gangs are just alike. More recently (Whittaker et al. 2020) extended this to contemporary gangs, finding different gangs adapted differently to social media use. Further research has found that levels of gang organization predict such variation (Moule Jr et al. 2014). Future research should further explore what gang characteristics drive associations between online and offline violence.

This study has several limitations. First, the bivariate Hawkes process used here only estimates Granger causality, in particular whether the event intensities of Facebook comments and shootings in the future are better predicted using shootings and Facebook comments from the past. We are not, for example, able to rule out the presence of a third confounding process that may cause online and offline events to co-cluster independently.

A second limitation is that our analysis of online-offline associations was limited to Latino gangs in a single city over a two-year period. To validate our findings, replications across different cities, social media platforms, and timeframes are necessary. This limitation raises questions about generalizability, particularly to other racial or ethnic gang groups, especially African American gangs.[2] Our data reveals behaviors similar in certain respects to those of members of African American gangs noted in Stuart's (2020) research, such as highly inflammatory language used against deceased individuals. But significant cultural differences, such as the lesser role of drill or trap rap in Latino gang interactions, were also evident. Future research should examine whether our findings apply across different racial and ethnic groups.

Third, we did not employ a full multivariate Hawkes process network that could consider second-order spillover effects. Consequently, critical aspects of gang culture such as geographic proximity and historical negative interactions were not included. The absence of these factors may lead to an underestimation of the relationship between online conflicts and offline violence. Nonetheless, our analysis identified a causal relationship, in terms of Granger causality, from shootings to online negative comments. Despite the informational limitations affecting both directions of analysis, the data suggests that the impact of offline events on online activity is more pronounced than the converse, highlighting an area for future research to expand upon by incorporating additional gang-related covariates.

Finally, our dictionary has limitations as well. Many gang-related comments, particularly those involving nicknames, were not detected. These nicknames often carry deep symbolic meanings-either expressing solidarity, as in "rest in peace," or used derogatorily, as in “rotz" or “burns," to provoke rivals. The inability of our dictionary to categorize these as negative interactions indicates a gap in our quantitative analysis. Future studies should strive to include these variations to more comprehensively capture the nuances of gang-related communications.

As social media use cements itself as a dominant form of interactions, more research is needed on the relationship between online and offline violence. Our study suggests that framing the relationship as governed by either spillover or performance is overly simplistic. The role of social media in gangs most likely involves both performance, violence, and contextual factors, such as the type and organization of the gang. Future research should investigate these factors. Addressing gang violence in the 21st century requires a comprehensive understanding of the impact of social media.

[2] Our understanding is that Asian gangs do not have a systematic presence in Chicago. According to the research team, white gangs no longer exist in the city as distinct entities, although there are a non-trivial number of white gang members in predominantly Latino gangs.

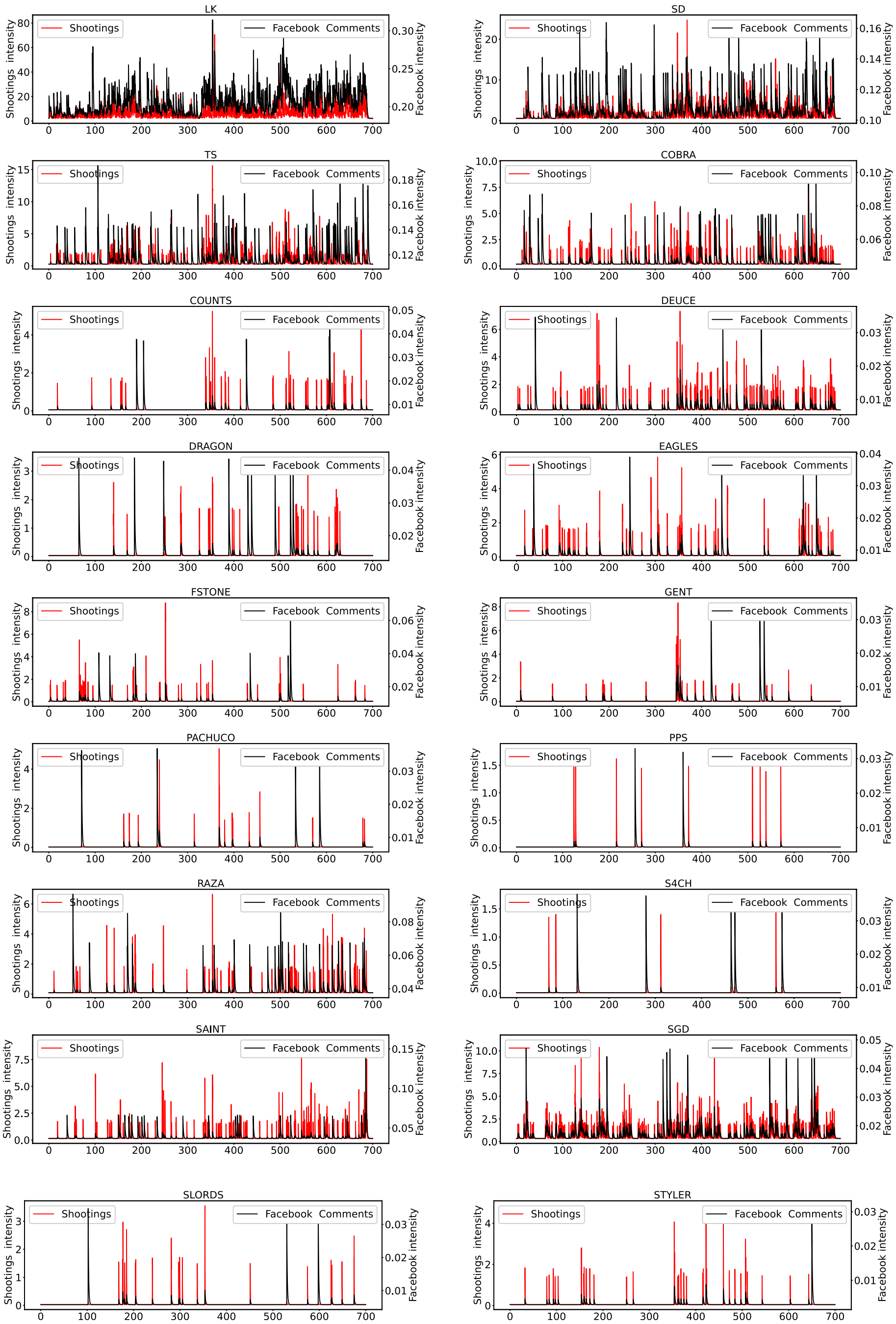

Fig. 6 Estimated conditional intensities of additional 31 gangs not shown in Fig. 4 with respect to time (in days)

Appendix

Remaining Plots of Fig. 6

In Fig. 6, we plot the estimated conditional intensities of the remaining 31 gangs not plotted in Fig. 4. It is important to note that, similar to our overall analysis of all gangs compared to the three largest gangs, these individual analyses also show variation. Specifically, some gangs exhibit high levels of both offline and online conflict (e.g., COBRA), while others display much less (e.g., KGB). Furthermore, some gangs

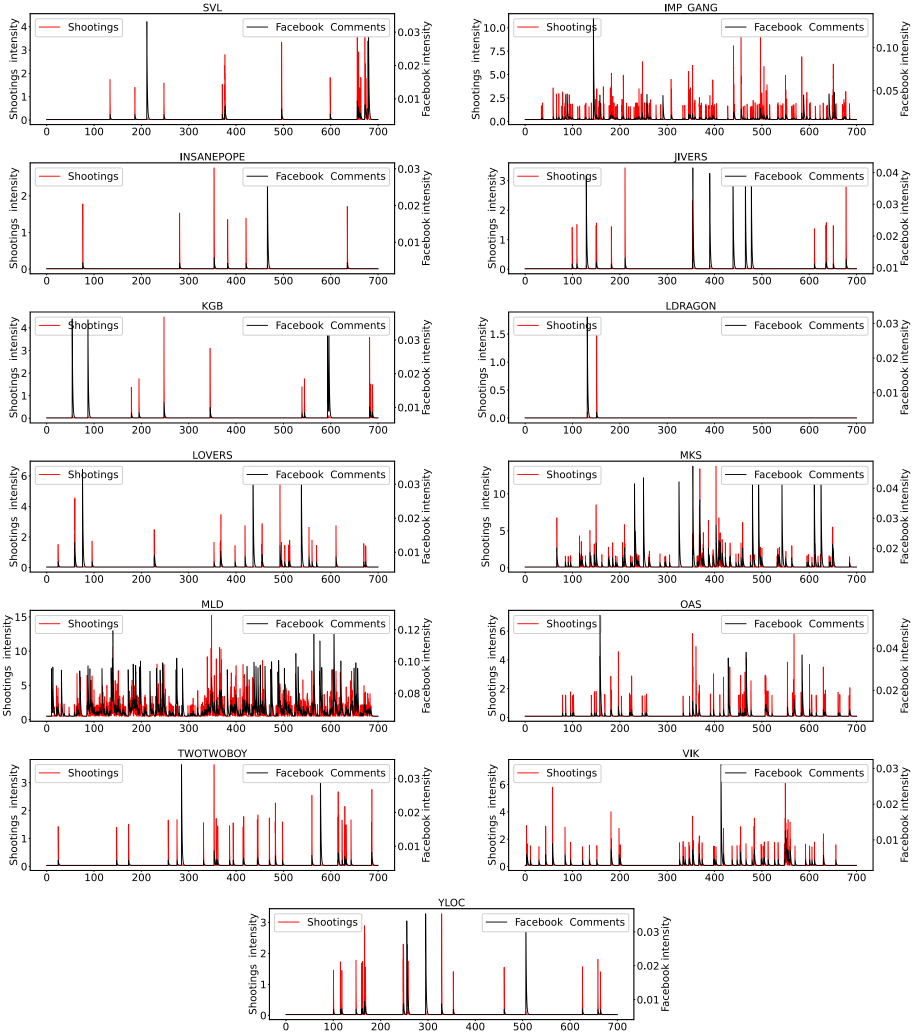

Fig. 6 (continued)

experience more online conflict than offline (e.g., STYLERS). There is also variation in the extent to which gangs are attacked both online and offline. Therefore, while our results provide an overall picture of magnitude and direction for all gangs, it is important to recognize that any individual gang may deviate from this pattern.

Gangs Full Names

In Table 9, we display the full names of the gangs analyzed throughout this paper along with the abbreviations used.

Table 9 Gang abbreviations and full names

Abbreviated name	Gang full name
AMBROS	AMBROSE
MKS	MILWAUKEE KINGS
MLD	MANIAC LATIN DISCIPLES
ASR	SIMON CITY ROYALS
GENT	HARRISON GENTS
OAS	ORCHESTRA ALBANY
BISHOP	BISHOPS
IMP_GANG	IMPERIAL GANGSTERS
PACHUCO	PACHUCOS
VIK	ASHLAND VIKINGS
INSANE POPE	INSANE POPES
PPS	PARTY PEOPLE
COBRA	SPANISH COBRAS
JIVERS	LATIN JIVERS
RAZA	LA RAZA
COUNTS	LATIN COUNTS
KGB	KRAZY GETDOWN BOYS
S4CH	SPANISH FOUR CORNER HUSTLERS
DEUCE	INSANE DEUCES
YLOC	YOUNG LATIN ORGANIZATION COBRAS
SAINT	LATIN SAINTS
DRAGON	INSANE DRAGONS
LDRAGON	LATIN DRAGONS
SD	SATAN DISCIPLES
EAGLES	LATIN EAGLES
LK	LATIN KINGS
SGD	SPANISH GANGSTER DISCIPLES
FSTONE	LA FAMILIA STONES
LOVERS	LATIN LOVERS
SLORDS	SPANISH LORDS
STYLER	LATIN STYLERS
SVL	SPANISH VICE LORDS
TS	TWO SIX
TWOTWOBOY	TWO-TWO BOYS

The Role that Age of the Victim Plays in the Model

Here we consider an alternative specification of the model where we investigate the sensitivity of results to age of the shooting victim. It may be the case that online conflict has a higher association with offline violence among younger gang members in Chicago. To assess such a hypothesis, we filter Chicago gang-related shootings by age of the victim into four groups: 20 years old or younger, between 20 and 30, between 30 and 40, and older than 40 years old. We then estimate the multivariate Hawkes process model independently for each age group, resulting in reproduction matrix elements $\alpha_{i,j}$ for each age category (using Stan and employing the same priors given in Eq. 16). We report the mean value of the reproduction matrix elements, as well as 95% confidence intervals, in Table 10.

From Table 10, we see that the mean values of the reproduction matrix do not vary substantially across different age categories. In addition, the corresponding 95% confidence intervals have considerable overlap across age groups. Thus given the present data, we are unable to conclude that variation in age is lined to variation in online-offline spillover of gang violence. However, given the limitations outlined in the discussion, this subject could be worth further investigation in the future.

Table 10 Mean and 95% CI of the reproduction matrix elements for different age categories (all 34 gangs combined)

Age of gang members (victims)	Matrix elements	Mean	95% confidence interval (CI)
Younger than 20	α_{11}	0.604	[0.587, 0.620]
	α_{12}	0.183	[0.061, 0.379]
	α_{21}	0.0004	[0.000, 0.001]
	α_{22}	0.017	[0.001, 0.051]
Between 20 and 30	α_{11}	0.603	[0.585, 0.620]
	α_{12}	0.110	[0.006, 0.348]
	α_{21}	0.002	[0.0001, 0.005]
	α_{22}	0.022	[0.002, 0.052]
Between 30 and 40	α_{11}	0.603	[0.587, 0.621]
	α_{12}	0.141	[0.008, 0.427]
	α_{21}	0.0005	[0.000, 0.001]
	α_{22}	0.026	[0.002, 0.068]
Older than 40	α_{11}	0.603	[0.586, 0.620]
	α_{12}	0.204	[0.013, 0.606]
	α_{21}	0.0003	[0.000, 0.001]
	α_{22}	0.061	[0.004, 0.180]

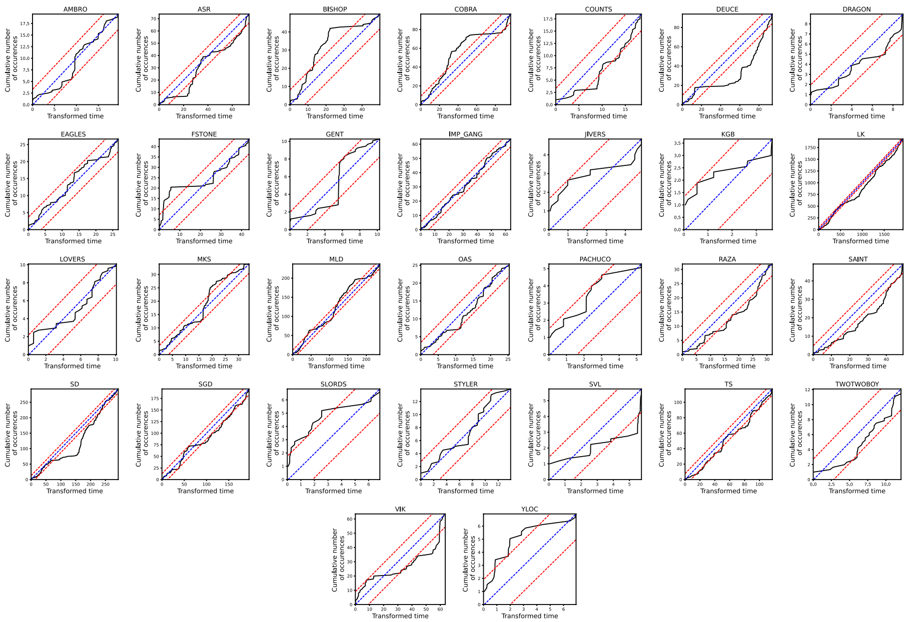

Fig. 7 Cumulative distribution of the rescaled data $\{\tau_i^1\}$ corresponding to online events (Facebook comments). The red dashed lines correspond to the 95% error bounds of the Kolmogorov–Smirnov statistics assuming a uniform distribution, while the blue dashed line corresponds to the mean cumulative distribution function of a uniform distribution. This plot excludes gangs that have less than 10 Facebook comments

Residual Analysis

Rescaled Residuals

Here we explore the goodness of fit of the Hawkes process model using residual analysis (Ogata 1988; Schoenberg 2003). Following the notation of Ogata (1988), we transform our data $\{t_i\}$ to $\{\tau_i\}$ following

$$\tau^k = \Lambda(t^k) = \int_0^{t^k} \lambda^k(s)ds, \qquad k = 1, 2, \tag{19}$$

where $k = 1$ corresponds to the online events, and $k = 2$ corresponds to the offline events. If the conditional intensity is correctly specified, then the transformed data $\{\tau_i^k\}$ are distributed according to a unit rate Poisson process. Thus one can assess goodness of fit of the model by applying a uniformity test to the transformed event times. One such test is a Kolmogorov–Smirnov (KS) test, where the cumulative distribution function of the rescaled data is compared to that of a unit rate Poisson process.

In Figs. 7 and 8 we plot the cumulative distribution of transformed times $\tau_i^k = \Lambda(t_i^k)$. The dotted red lines represent the 95% error bounds of the Kolmogorov–Smirnov (KS) statistics, assuming a uniform empirical distribution.[3]

[3] Here we have filtered out gangs with fewer than 10 events from the residual analysis.

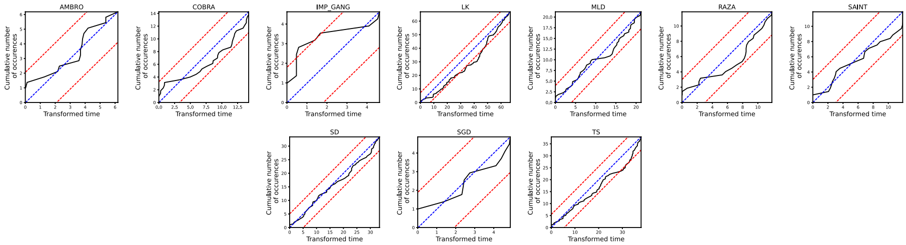

Fig. 8 Cumulative distribution of the rescaled data $\{\tau_i^1\}$ corresponding to shooting events. The red dashed lines correspond to the 95% error bounds of the Kolmogorov–Smirnov statistics assuming a uniform distribution, while the blue dashed line corresponds to the mean cumulative distribution function of a uniform distribution. This plot excludes gangs that have less than 10 shooting events

In the Figs. 7 and 8, we compare the cumulative number of the rescaled events (black line) with the 95% confidence bounds of the KS statistics assuming a uniform distribution. We find that the estimated intensity provides a good fit to the shootings data, where only slight deviations outside the 95% bounds are seen for several gangs. In the case of the online data, we observe deviations for around half of the gangs (for example BISHOP, COBRA, DEUCE and LK). We note that the fit of the model would likely be

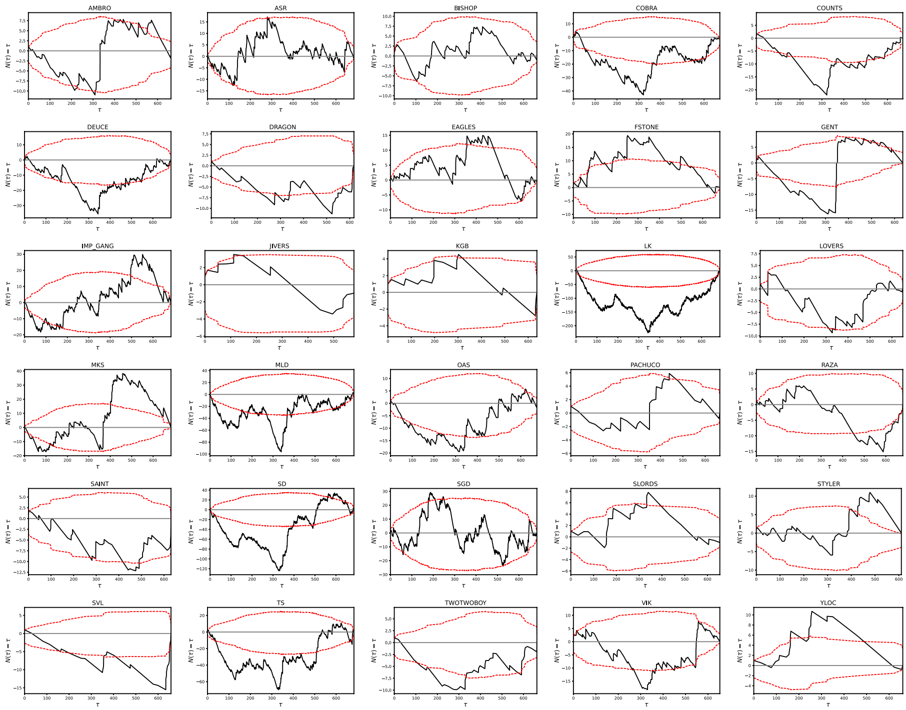

Fig. 9 Normalized cumulative distribution for the superthinned data that corresponds to FB comments (black straight line). The red dashed lines account for the 95% error bounds for a homogenuous Poisson process based on 10000 simulaltions of a homogenuous Poisson process with the same rate as the one used for superthinning. We have not considered gangs that have less than 10 FB comments

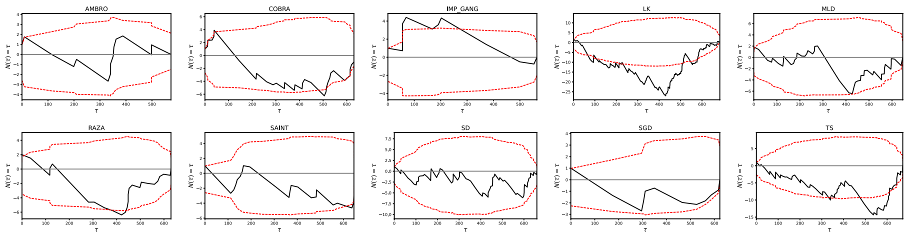

Fig. 10 Normalized cumulative distribution for the superthinned data that corresponds to shooting events (black straight line). The red dashed lines account for the 95% error bounds for a homogenuous Poisson process based on 10000 simulaltions of a homogenuous Poisson process with the same rate as the one used for superthinning. The gangs that have less than 10 shooting events were disregarded

improved by allowing the reproduction matrix to vary across gangs, however this would also lead to over-fitting and higher variance in the estimated parameters.

Super-Thinning

In this subsection, we use another method to assess the goodness of our fit. The method we use is called superthinning. It involves both thinning and superposition (Schoenberg 2003; Clements et al. 2012). We first proceed by thinning the points $\{t_i\}$ by keeping each point individually with probability $min\{\frac{k}{\tilde{\lambda}(t_i)}, 1\}$, where $\tilde{\lambda}$ is the estimated conditional intensity, to obtain a thinned residual process Z_1. Next, we simulate a homogeneous Poisson process with rate k and keep each point with probability $max\{\frac{k-\tilde{\lambda}(t_i)}{k}, 0\}$. The latter results in a residual process Z_2. The points of the residual point process $Z = Z_1 + Z_2$ obtained by superposing the thinned residuals and the simulated Poisson process are called the superthinned residual points. We choose the parameter k to be the mean of the conditional intensity $\tilde{\lambda}$. We visualize the goodness of fit using superthinning for the online data in Fig. 9 and the offline data in Fig. 10. This is done by comparing the superthinned data to the 95% bounds of a homogeneous Poisson process based on 10000 simulation of a homogeneous Poisson process using the same rate used for the superthinned data. We observe that the estimated intensity provided a good fit for most of the shooting data with some deviations from the 95% bounds of the homogeneous Poisson process for some gangs (such as LK). On the other hand, for the online data, we found that around half of the gangs showed deviations from the 95% bounds, e.g., TS, SD and LK (a similar result to residual analysis in the previous section).

Acknowledgements This research was supported in part by NSF grant ATD-2124313, ATD-2317397, SCC-2125319 and AFOSR MURI grant FA9550-22-1-0380. Partial support for this research also came from a Eunice Kennedy Shriver National Institute of Child Health and Human Development research infrastructure grant, P2C HD042828, to the Center for Studies in Demography & Ecology at the University of Washington.

Declarations

Conflict of interest The authors declare that they have no conflict of interest

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