The exacerbating effect of police presence: A multivariate point process analysis of the Naxal conflict

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Abstract

The effect of police presence is an important consideration when designing counter-insurgency activities. While there has been much empirical research investigating the effects of counter-insurgency in a military setting, the effect of police presence in countering political dissidents has seen more limited attention. We argue that police presence at violent events is likely to exacerbate subsequent levels of violence rather than reduce them. To assess the validity of this claim we analyze a unique police dataset from the Indian state of Andhra Pradesh, which details the timing and location of police-recorded politically motivated violent offenses attributed to Naxals over a ten year period. The data also includes an indicator to determine whether or not police are present at each event, which we use to measure the exacerbating effect of police presence. Our analytical strategy is inspired by recent literatures concerning crime and political violence that examine event interdependence at disaggregated levels of analysis. We calibrate a series of novel multivariate point process models, which are designed to test a series of hypotheses. Our results show that: 1) the Naxal conflict displays patterns of spatio-temporal clustering; 2) police presence at violent events exacerbated the conflict, leading to more events than would have otherwise occurred, at least in the short term; and 3) the space-time regularities can be usefully employed to predict the likely locations of future events.

Keywords: Space-time analysis, conflict, policing, point process modelling, Hawkes process.

1. INTRODUCTION

Political violence clusters in space and time. To what extent does policing affect this clustering? While there have been a great number of studies into patterns of violent and conflict events[1] in space and time, most of these have not accounted for the activities of those whose objective is to prevent such events from occurring in the first place. In spite of this omission, geographically focused policing initiatives often deploy police to conflict and crime hotspots in the expectation that this will reduce the opportunity for subsequent events to occur in that area. However, in some cases, this might not be the case. For event types such as rioting, civil disorder, and political violence, the deployment of police might even exacerbate the relationship between police and non-state actors, risking an escalation in the number of violent events. In such cases, accounting for police presence during an event is crucial in understanding the police's impact on levels of political violence.

In this article, we address this shortcoming by drawing upon a key implication from the repression-dissent nexus and backlash literatures (Lichbach, 1987; Moore, 2000). Government decisions to deploy police forces and non-state actor choices of levels of political violence are the result of strategic interaction. Governments are highly likely to respond to non-state actor violence with their own uses of force, because they will view this as the most efficient means of deterring future challenges (Davenport, 2007). We contend, in line with prevailing wisdom, that more police action is highly likely to have the unintended consequence of exacerbating rather than ameliorating subsequent levels of non-state actor violence, perpetuating a cycle of violence (Poe and Tate, 1994).

We test the implications of this argument through the quantitative modeling of a unique police dataset from the erstwhile state of Andhra Pradesh in India[2]. These data describe the timings of attacks on civilians and police by Naxal dissidents at a daily level of resolution over a 10-year period. In essence, we consider all events perpetrated by Naxals or alleged Naxals as insurgent activ-

[1]We refer to political violence and conflict events interchangeably throughout this article to indicate violent events carried out by non-state (here Naxal) actors.

[2]The data refers to the period 2000 to 2010 prior to the separation and creation of the state of Telangana from Andhra Pradesh on June 2nd 2014. We focus on the districts that form the new state of Telangana. With more than 35 million residents, Telangana is India's 12th (of 29) largest state.

ities because they are recorded as such by the police. Distinguishing between events that occur with and without the presence of police, we model the timings of both types of events simultaneously using a multivariate point process model. The particular type of model we employ, known as a Hawkes process, exploits regularities in the timings and locations of events to estimate the likelihood that an event will occur conditional on events that have already been observed. Our models use only the timings and locations of violent events attributed to Naxals by police. Nevertheless, we show that such simple models are capable of testing theoretically-derived hypotheses relating to the impact of police presence as well as to the timing and locations of conflict events via our case study in the Indian subcontinent. We also perform an out-of-sample test of our models.

Our study contributes to a number of theoretical perspectives that have been prevalent in recent literature. First, we contribute to the analysis and quantification of endogenous processes within long-running conflicts using a disaggregated perspective. An emerging literature is beginning to focus on the interdependencies between events—for example, by considering the causal effect of prior events on the likelihood of future ones—rather than identifying purely structural factors that create conditions conducive to conflict. Second, we provide further evidence for the phenomenon of spatio-temporal clustering of conflict events. By investigating the spatio-temporal properties of violent activities of political dissidents in a largely rural area within a newly industrialized economy, we provide a test of this phenomenon in a novel scenario, which serves to emphasise that this phenomenon may be more consistent and widespread than previously thought. Finally, and representing the principal research question of this study, we investigate the escalatory impact of police in addressing political violence and quantify the extent to which the presence of police exacerbates subsequent levels of conflict. This is a particularly important concern when managing police resources to counter the threat posed by political dissidents. Although a number of previous studies have considered the role and effectiveness of military resources when countering insurgent violence, very few studies to our knowledge have provided empirical analyses for a police force faced with such long-running violence. Police forces can have fundamentally different functions and objectives to a military (Perliger et al., 2009) and it is their influence on such conflicts that we seek to understand in this article.

A point process analysis is possible due to the daily level of resolution of the data. This is advantageous over time series approaches—which have, to date, been the principal means of analysing the rate of political violence, e.g. Enders and Sandler (2000)—as it retains a high-level of disaggregation. A number of recent studies have applied similar models to a range of crime types, insurgent activity, and terrorist attacks (Lewis et al., 2011; Benigni and Furrer, 2012; Porter and White, 2012; Zammit-Mangion et al., 2012; White et al., 2012; Mohler, 2013; Tench et al., 2016). This article contributes to this literature from a methodological perspective by proposing novel multivariate models that incorporate spatial effects and which enable a comparison between events that involve police and events that do not. In addition, our model evaluation procedure is a further contribution: we estimate standard errors of model parameters via a bootstrapping procedure and test our model performance with an out of sample prediction task.

This article proceeds as follows: first, we outline in detail the three theoretical perspectives to which our analysis contributes, deriving four testable hypotheses. Next, we introduce our case study—the Naxal movement and their armed struggle against the state in the Indian state of Telangana—and discuss the policing challenges in more detail. We describe the government's response to the dissidents and explain why a quantitative analysis might shed more light on the conflict. We then construct a series of models that are capable of capturing the local dynamics of police recorded Naxal attacks and so-called police encounters. We present our results and discuss what they imply for policing of political violence, both with respect to the particular case study and more generally. In addition, we assess with an out of sample analysis whether such models might be usefully incorporated into planning police responses.

2. THEORY AND HYPOTHESES

2.1. Disaggregating Political Violence

The disaggregated perspective in the study of political violence has recently been widely promoted (Cederman and Gleditsch, 2009; Blattman and Miguel, 2010; Behlendorf et al., 2012; Donnay, 2014). Studying violence at the local level can help identify internal consistencies (such as feedback processes), point to the drivers of the conflict, and highlight reasons for its apparent intractability, all of which may be difficult to do with a more aggregate perspective. Although the onset of conflict might have causes associated with structural factors—the study of which has dominated the literature relating to civil conflict at both the national level (Fearon and Laitin, 2003) and the sub-national level (Buhaug et al., 2011)—the day-to-day nature of the conflict, its resulting duration, and opportunities for conflict resolution can depend more on endogenous processes within the conflict itself, rather than factors external to it.

Disaggregation of conflicts into their constituent events can occur in a number of ways. Spatial disaggregation, whereby events might be mapped to their specific locations (Donnay, 2014; Linke et al., 2016), or to within areas where those events occur (Braithwaite and Johnson, 2015), enables the investigation of the geographic distribution of conflict events, highlighting areas that are more at risk. Temporal disaggregation, whereby the precise timings of events are analyzed, can be used to identify trends in the intensity of the conflict. Disaggregation of conflict events can also be achieved by accounting for the different actors involved in each event and investigating the differences, if any, between events that involve different participants. We combine all three of these approaches in this study.

In the sections that follow, we first discuss theoretical advances that have been made as a result of disaggregating event data with respect to space and time, in which the phenomenon of spatio-temporal clustering of events can lead to insights regarding the likely locations and timings of future events. Next, we consider disaggregation with respect to the actors involved in those events. Although few studies have considered the impact of police on the spatio-temporal clustering of crime and political violence, a number of previous studies have explored the role of the military in countering threats during insurgencies at disaggregated levels of analysis and it is these that we largely discuss.

2.2. Spatio-temporal Clustering of Conflict and Crime Events

Political violence and crime events have been shown to cluster in both space and time. The literature on repeat and near-repeat victimisation is especially well developed. Here it is shown that crime, particularly burglary, is more likely to be observed in close spatial and temporal proximity to a prior event than at any other randomly selected time or location (Johnson et al., 1997, 2007a). Police forces have adopted operational strategies exploiting this consistency in an effort to deploy their resources to the areas most at risk and where the most benefit from police presence might be realized (Pease, 1998; Bowers et al., 2004;

Johnson et al., 2007b). The phenomenon of crime clustering has been observed for a number of different crime types and, importantly in the present context, for crimes relating to political violence and civil conflict.

Focusing first on temporal clustering, analysis of the timings of events associated with human conflict, terrorism, and insurgencies has shown that inter-event time distributions can exhibit heavy-tails, a phenomenon that is remarkably robust at the conflict level (Bohorquez et al., 2009; Johnson et al., 2011; Clauset and Gleditsch, 2012; Johnson et al., 2013; Picoli et al., 2014). That is, violent events are likely to occur in bursts together with intermittent periods of inactivity. Observing a single event increases the likelihood of observing a second event for a short time period. Similar investigations have shown that inhomogeneous and history-dependent point process models improve upon simple Poisson process models in accounting for the timings of terrorist attacks and insurgent violence (Lewis et al., 2011; Mohler, 2013; Zammit-Mangion et al., 2012; Porter and White, 2012; White et al., 2012).

Attempts to explain such clustering of activities typically consider the decision-making and operations of the actors committing them. Employing a rational choice perspective, Townsley et al. (2008) argue that insurgents are more likely to commit further attacks after a prior successful attack due to the efficacy demonstrated by the first attack and because, by doing so, insurgents can minimize the effort expended in planning new attacks. Insurgents may also be more likely to commit further attacks shortly after a prior attack because they will already have access to the weapons, organizational support, and other such capabilities required to carry them out.

Counterinsurgent activity may also be temporally clustered as it responds to variation in political strategies aimed at diminishing the threat from insurgents, the actions of insurgents, and other intelligence obtained. In some cases, the counterinsurgent activities have been shown to be even more time-autocorrelated than the insurgent events themselves (Braithwaite and Johnson, 2012; O'Loughlin and Witmer, 2012).

In accordance with this prior work on the temporal clustering of political violence, we state our first hypothesis:

Hypothesis 1: Temporal clustering. Conflict events, regardless of whether police are present, are expected to exhibit temporal clustering, whereby the risk of a further event is elevated for a period of time after an initial event.

The role of geography in facilitating the internal dynamics of long-running conflicts has also been investigated and robust patterns of both spatial and spatio-temporal clustering have been identified. Inspired by evidence of spatio-temporal clustering in a range of different crime types, Townsley et al. (2008) and Johnson and Braithwaite (2009) investigate different types of insurgent activity in Iraq and show that pairs of events are much more likely to be located near to each other in both space and time when compared to a null hypothesis of event independence.

Spatio-temporal clustering of events leads to dynamic hotspots of insurgent activity, in which a higher than expected number of events occur over a short period of time within a particular geographic area. These hotspots may grow, diffuse, or decline over time. Such hotspots of insurgent activity have been identified using a variety of analytic techniques in Afghanistan and Pakistan (O'Loughlin et al., 2010; Zammit-Mangion et al., 2012), Spain and El Salvador (Behlendorf et al., 2012), and the Northern Caucasus (O'Loughlin et al., 2011; O'Loughlin and Witmer, 2012). In all cases, strong localized patterns of conflict are demonstrated, which can perhaps be used as the basis for the prediction of future events (Zammit-Mangion et al., 2012). That is, future events are anticipated to be observed in close spatial proximity to previous events, rather than farther away.

Moreover, studies have shown that the risk of a particular location experiencing a conflict event decays with distance to prior events or anticipated hotspots. For example, O'Loughlin and Witmer (2012) show that retaliation between insurgents and counterinsurgents decays spatially across geographically neighbouring areas, Raleigh and Hegre (2009) show that future conflict events are more likely to be closer to the previous event than farther away, and Weidmann and Zürcher (2013) provide evidence that the impact of conflict events decays exponentially in both space and time. Consequently, our second hypothesis states:

Hypothesis 2: Distance decay. Distance is expected to have a diminishing influence on the effect of prior events on subsequent events.

2.3. Backlash Effects and Police Presence

To this point, we have suggested that levels of violence may be self-reinforcing, with new events more likely to occur at close proximity in time and space to prior events. Both of the hypotheses laid out thus far follow conventional wisdom from the literature. In moving forward, we look to additionally identify a role for government police forces in affecting the likelihood of insurgent violence. To do so, we draw upon a key implication from the repression-dissent nexus and backlash literatures: that (especially coercive) government actions are highly likely to exacerbate rather than deter subsequent insurgent violence (Lichbach, 1987; Poe and Tate, 1994).

Deploying police to particular locations predicted to be at a high risk of experiencing crime is a common method of organising police resources. Some studies have sought to demonstrate the reduction in crime rates as a result of such targeted deployment (Sherman and Weisburd, 1995; Ratcliffe et al., 2011; Braga and Weisburd, 2012; Mohler et al., 2015). The presence of police is thought to reduce available opportunities for crime through the presence of capable guardians and by increasing the perceived risk of apprehension of potential offenders. These studies examine the efficacy of police patrols, in which the police officers do not have a specific crime or target to investigate. However, when the police take a more active role in targeting and disrupting suspected offenders by imposing sanctions, the possibility for backlash effects can arise. Backlash effects occur when police sanctions motivate a sense of defiance among a group of potential offenders, who respond by causing more crime than would have occurred without the police intervention. Such effects are expected when the sanctions introduced by police: stigmatize the actors, rather than the act; are considered by the suspected offender to be unjust; and/or are administered by a perceived illegitimate actor (Sherman, 1993).

A number of recent studies have shown the presence of backlash effects during political violence in response to military counter-insurgency. Tit-for-tat behavior, whereby an attack by one side begets an attack by the other, has been identified in a number of conflicts (Haushofer et al., 2010; O'Loughlin and Witmer, 2012; Linke et al., 2012; Tench et al., 2016). Some studies have also distinguished between the type of actions adopted by counter-insurgent forces when facing insurgent violence and have shown that, while some actions appear to have a placating influence, other types of counter-insurgent activity can increase the risk of subsequent attacks (LaFree and Dugan, 2009; Braithwaite and Johnson, 2012; Toft and Zhukov, 2012; Eastin and Gade, 2016). This body of evidence suggests that aggressive and more indiscriminate counter-insurgency actions are likely to result in more subsequent attacks (see also Condra and Shapiro (2012)).

A distinguishing feature of the case study considered in this article, in contrast to many of the examples cited above, is that it is the police force who were tasked with responding to the Naxal campaign, albeit using paramilitarized units. There have been very few quantitative analyses of the backlash effects resulting from police actions in such settings. One exception is Behlendorf et al. (2012), who find that ETA and FMLN terrorists in Spain and El Salvador, respectively, are more likely to avoid targeting military units during localized bursts of terrorist activity in order to avoid provoking retaliation, but do not find a similar effect for police units.

Police forces have very different behaviors and constraints to a military in responding to violent events. Perliger et al. (2009) argue that a policing response to terrorism is not only more justifiable from a legal perspective in democratic countries, but is also a more effective way of addressing the problem. If this is indeed the case, then we might expect to see differences in the internal dynamics of a protracted insurgency such as the Naxal case when compared to scenarios involving the military, where much prior research on the endogenous dynamics of subnational insurgencies has been focused. Nevertheless, in the absence of such a well-defined body of evidence in the policing literature, we formulate our third hypothesis in accordance with the evidence available in a military setting. We hypothesise that counter-insurgency actions instigated by the police cause a backlash effect in which the likelihood of subsequent attacks increases for a short period of time.

As will be explained in what follows, for our case study, we are unable to distinguish between counterinsurgent activity and attacks by the insurgents that are targeted at police. Instead, the variable we explore is whether or not police were present at each event. Although this variable does not enable us to offer a clear picture of counterinsurgent activity and strategy, it does allow us to examine the influence of police presence on subsequent attacks. There are two distinct advantages in exploring the extent to which a variable on police presence—rather than on counterinsurgent activity—allows us to model the likelihood of future attacks. First, police presence is easier to capture during outbreaks of political violence as it can be collected from news reports describing clashes between opposing groups. Second, information about police presence at each event can be obtained without close collaboration with one side of the conflict, such as the police, whereby descriptions of each event and the counterinsurgent activities sanctioned by that side are relied upon. Police presence is a more objective measure that can be validated by multiple sources. In short, when predicting the likelihood of future attacks in other conflict scenarios, police presence is easier to operationalise than detailed information on potentially classified police operations.

In order to derive a hypothesis on police exacerbation, we consider the two different causes for police presence at an event. If an event with a police presence was caused by a counterinsurgency action, then we might expect to observe a backlash effect due to the reasons outlined above. On the other hand, if an event with a police presence was caused by insurgents targeting police, then we might also expect a subsequent increase in the likelihood of future attacks. This is because insurgents will either be buoyed by the success of an attack on the police and look to replicate this success or, if the attack failed and the police fought back, then we might again observe backlash effects as the insurgents look to retaliate. Thus, our third hypothesis states:

Hypothesis 3: Police exacerbation. Police presence at an event is expected to increase the likelihood of further events for a short period of time.

Our final hypothesis considers the scenarios under which we might observe an increase in the likelihood of attacks with a police presence. Police presence as a counterinsurgent action can be caused by police responding to prior attacks in order to disrupt insurgent capability and make arrests from prior crimes. Police retaliation to insurgent attacks can also be an important signal to civilians, as the police aim to deter civilians from joining the insurgency. Events with a police presence that are brought about by police being targeted by the insurgents, may also be more likely in the aftermath of prior attacks, as insurgents are emboldened by the success of prior attacks and seek to target more ambitious targets such as the police. Therefore, our final hypothesis states:

Hypothesis 4: Police reaction. Conflict events that do not involve police are expected to increase the likelihood of future events that do involve police for a short period of time.

Having established the motivation for the study, and the hypotheses to be tested, we next provide a brief description of the Naxal movement to orient those unfamiliar with the conflict.

3. THE NAXAL MOVEMENT IN ANDHRA PRADESH AND TELANGANA

The Naxal movement, often also referred to as left-wing extremism or the Maoist movement, was declared the single biggest internal security challenge faced by India by the Prime Minister, Manmohan Singh, in 2006 (Dubey, 2013). Its roots can be traced back to the 1946-1951 Telangana movement, an armed agrarian insurrection demanding land reform legislation (Dhanagare, 1974). The early Naxal movement was fuelled by a number of grievances against the state including economic inequality; underdevelopment; poor governance; ruthless exploitation of natural resources by the state; poverty; and a lack of access to the justice system (Ahuja and Ganguly, 2007; Basi, 2011).

The state crushed the early Naxal movement in the 1970s, forcing it underground. Regaining strength in the early 1980s, the movement spawned several splinter groups, including the People's War Group (PWG) in Andhra Pradesh and the Maoist Communist Centre (MCC) in Bihar (Kujur, 2008). The PWG was committed to armed struggle against the state, engaging in acts of kidnapping, extortion, and elimination of civilian and political opponents (Mitra, 2011). The late 1980s witnessed an unprecedented increase in violence in Andhra Pradesh after the PWG began directly targeting the state and attacking the police.

In Andhra Pradesh (which, at the time, contained the present-day state of Telangana), the state response was to paramilitarize the police and improve intelligence apparatus via the formation of the Special Intelligence Branch. The Greyhounds are a special commando unit manned by officers selected from the local civil police and trained in guerilla warfare. They were specifically established and tasked with countering the threat posed by dissidents. Members of the unit return to civil policing after their stint in the special commando unit. The Greyhounds were well-equipped, trained in guerrilla warfare, and established a reputation for aggressive counterinsurgency tactics, which included brutal search and cordon operations, torture, beatings and the detainment and displacement of entire villages (Ahuja and Ganguly, 2007; Balagopal, 2007). Although a special unit, overall command and control of the greyhounds rests with the state police. Furthermore, anti-naxal operations are often conceived jointly at a strategic and operational level between local police and the special units, facilitated by the fact that they are all civil police officers. It is thus nearly impossible to separate out greyhound activities from the general police actions recorded in the data.

The formation of the People's Liberation Guerrilla Army in December 2000 was a turning point in the escalation of violence in the Maoist movement, enabling the Naxals to better organise their military capabilities and improve their recruitment drives (Dubey, 2013; Reddy, 2010). The 2004 merger of the PWG and the MCC to form the Communist Party of India (Maoist) ushered in a new pan-India Naxal movement with a centralized leadership and a unified command and control structure. In response, the Andhra Pradesh government called a six-month hiatus to the conflict in an attempt to conduct peace talks. However, following the breakdown of peace talks in early 2005, the state resumed its uncompromising stance. Attacks by both insurgents and counter-insurgents continue to the present day, albeit more recently restricted to smaller pockets of the country (Banaji, 2010).

The police's operational strategy has focused on eliminating suspected Naxals in extrajudicial killings, arresting insurgents, and encouraging voluntary surrenders of prominent Naxal leaders (Bhatnagar et al., 2012). Eventually, the government recognized the need to address socio-economic problems and adopted a development-focused approach with a view toward eroding popular support for the Naxals, albeit together with stringent counterinsurgency measures (Ramana, 2011). These measures are said to have weakened the movement considerably (Sahni, 2010; Mandar, 2004). Despite a surge in Maoist activity in the north Telangana districts in late 2009, the police claimed they were able to restrict the Naxalites' bid to reclaim their stronghold in this area (Reddy, 2011).

At present, Naxal activity is largely confined to two districts in present-day Telangana, a dramatic change from the situation in 2005 when nearly all of the 23 districts in Andhra Pradesh were considered to be highly or moderately affected (Chakravarti, 2009). While the situation continues to cause concern for government and security forces, the total number of casualties (civilians and security forces) associated with the movement has been in steady decline.

In spite of this recent decline, this long-running conflict has often been viewed as intractable by both sides. The literature discussed in Section 2 demonstrates how statistical models capturing fine scale behaviors can contribute to our understanding of such conflicts. Inspired by this work, we seek to contribute to the understanding of the Naxal conflict via the use of stochastic point process models.

4. DATA

A unique dataset of police recorded Naxal related crimes and attacks between 2000 and 2010 was provided by the Andhra Pradesh police. This included every incident of Maoist-related violence or threat recorded in police stations within the present-day state of Telangana, with a daily level of temporal resolution.

First, the data were sanitised, cleaned and systematically coded in categories similar to standard open source terrorism datasets, such as the Global Terrorism Database (GTD). The data includes events that were recorded by the Andhra Pradesh police as Naxal related, regardless of whether they were criminal, political or economic offenses. We restrict our attention to the following crime types: armed attacks, exchanges of fire (between police and Naxals), threats, explosions, attacks, arson, abductions, physical destruction, shootouts, murder, or any combination thereof. Events that could not be coded into one of these crime types (such as theft) were excluded from the analysis. Although some of the included event types would not ordinarily qualify as a terrorist incident under the criteria set by GTD (such as threats), our crime type definition reflects events that capture the police's understanding of and interaction with the violent nature of the conflict.

Since the data are police recorded, they are dependent on victim reporting behavior, police operational norms, legislative changes, changes in formal recording rules and politicization of crime, all of which affects how and what is recorded as crime (Maguire, 2007; Behlendorf et al., 2016). Such limitations are typical of all studies using police recorded crime data. One further limitation of the data, which is also true of all official terrorism statistics, and which is noted by LaFree (2010), is the absence of a standard definition of terrorism accepted by all. This implies that the police can and often do attribute non-violent or other criminal actions committed by known terrorist organisations as terrorist events for political or other reasons. Despite these limitations, the systematic and comprehensive nature of the data at the state level provides a novel opportunity to utilise official, event-level data collected during an insurgency. It captures all Naxal related violent events as perceived by the field actors that respond to them.

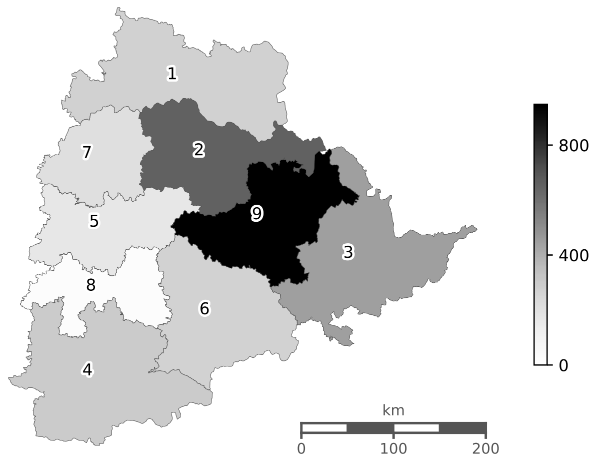
The crime type described as "exchanges of fire" refers exclusively to exchanges between (suspected) Naxals and police. Police presence during such an event arises due to two principal reasons: either the Naxals have targeted the police, who then fire back, or an exchange of fire results from a counterinsurgency operation initiated by the police. While there are no official sources or records describing state counterinsurgency policies or specific police strategy or operations, field research with police officers (Belur, 2010) and subsequent fieldwork conducted in left-wing extremist affected areas, has indicated that the killing of unwanted persons (in this case, Naxals) in shootouts was actively undertaken by police officers during periods when state/police policy was to adopt a strong counterinsurgency approach. These extrajudicial killings or 'encounters' are invariably recorded as exchanges of fire between the non-state actor and the police. The standard description of encounters is that the police either warn the 'criminal' to surrender, who then retaliates by firing on them, or the police are ambushed by the criminal (in this case, Naxal), but the latter dies in the resulting crossfire. This is the only way in which extrajudicial killings can be legally justified (Belur, 2010).

For the purposes of this article, we separate events in the dataset into those recorded as exchanges of fire and all other events. Although it is impossible to capture the underlying causes and motivations of the police during such exchanges of fire, separating the events in this way enables us to examine the distinction between the events that involved the presence of the police and those that did not. In this way, we can identify the effect that police events have on the conflict and contrast that effect with other events. In total, there were 2,592 events without police and 700 exchanges of fire (i.e. events with police presence) contained in the dataset. These were the events used in our analysis.

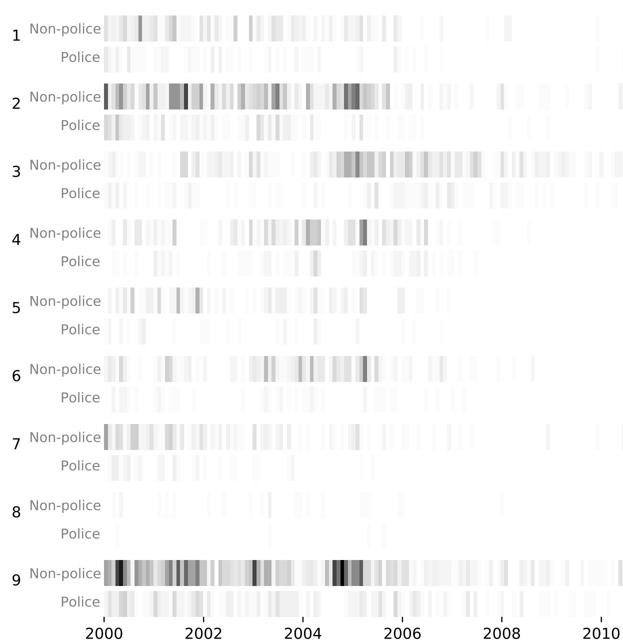
The events were also geo-referenced, enabling disaggregation of the conflict in space. In this article, we take as our spatial units of analysis the nine districts of Telangana, which is where the majority of events were geo-referenced. Although these districts are quite large in geographic extent (particularly when compared to previous studies on the geographic analysis of crime in urban areas), it is important to bear in mind that these regions are mostly rural with low population densities. Moreover, these districts represent geographic regions over which police chiefs routinely make deployment decisions. This ensures that our analysis is of relevance to operational decision-making. Figure 1 illustrates the geographic and temporal features of the data. Subfigure (a) maps the nine districts in Telangana and shades them according to the number of events in each district (with darker shading corresponding to more events). This map serves to emphasise the units of analysis—and the relationships between them—that we model. Subfigure (b) shows the temporal profile of the two event types of interest: those without police presence (labelled as *non-police*) and those with police presence (labelled as *police*). These plots show weekly event counts over the 10-year time period of the study. They demonstrate the extensive temporal variation in the intensity of event occurrence in the different regions. Furthermore, depicting the temporal distribution in this way shows prolonged areas of dark shading intersected with areas of lighter shading for many districts. This suggests the presence of temporal clustering, in accordance with Hypothesis 1. It is this phenomenon that our models described in the next section seek to explain. Moreover, our models provide a formal statistical investigation of this temporal regularity. For each of the nine districts, we model the intensity of both police events and non-police events, requiring a family of eighteen models. A series of such families are described in the next section.

5. MODELS

We model the Naxal insurgent campaign with a series of multivariate point processes. Such models have recently proved popular in the study of crime and security-related event data (Lewis et al., 2011; Benigni and Furrer, 2012; Porter and White, 2012; Zammit-Mangion et al., 2012; White et al., 2012; Mohler, 2013; Tench et al., 2016). The models we propose differ from these previous studies with respect to a number of important facets. First, our models are multivariate, meaning that different types of events are modelled simultaneously, enabling the assessment of whether certain types of events have distinct dynamics to



(a) The spatial distribution of events.



(b) Weekly density of police and non-police events for the nine regions under investigation.

Figure 1: The spatial and temporal distribution of police and non-police events over each of the nine districts under investigation. The digits 1-9 in subfigure (a) can be used to locate the temporal distribution in geographical space shown in subfigure (b). In both cases, darker shading corresponds to more events.

others. Second, the multivariate structure of the model enables the intensity of certain types of event to be dependent upon not just the occurrence of events of the same type, but on events of a different type. As we will show in what follows, this enables exchanges of fire and events that do not involve police to have different excitation dynamics. In short, we model the temporal interaction between events of different types. Third, we examine spatial interactions across different event types by modeling the conflict separately in each of the nine districts within the state of Telangana.

We additionally offer two perspectives on the evaluation of such models that have rarely been employed in previous point process studies concerning crime and security related phenomena. We estimate standard errors associated with each parameter via a parametric bootstrap procedure—a technique that has been shown to provide superior error estimates for similar point process models (Wang et al., 2010)—and we assess the predictive capability of our model via an out of sample test. This is in line with recent research in Criminology (Bowers et al., 2004; Mohler et al., 2011) and Political Science (Ward et al., 2010). These methodological contributions speak to the issue of how useful Hawkes process models might be in predicting the likelihood of events in theatres of conflict. We begin, however, by explaining how our models are derived.

We consider a multivariate point process in which different types of events are modelled as separate processes. To enable this, we denote each event i by (t_i, s_i, p_i), where t_i is the time at which event i occurs, s_i is the spatial region in which it occurs (encoded as an integer between 1 and 9 to represent each of the nine spatial regions), and p_i is a binary variable to determine whether police were involved in event i (in which case $p_i = 1$) or not (in which case $p_i = 0$). Then, we model the intensity function for each spatial region for each event type as a *Hawkes process* comprising of a *background rate*, which describes the likelihood of an event occurring in the absence of any previous events, and a *triggering kernel*, which describes how the likelihood of events changes with prior events that have occurred (Hawkes, 1971) (see Supplementary Materials accompanying this article for more background information).

Thus, the conditional intensity of events of type p (where $p = 0$ corresponds to events not involving the police and $p = 1$ corresponds to events involving police) within spatial region s (for $s = 1, 2, ..., 9$) is given, in its most general form, by

$$\lambda_s^{(p)}(t) = \mu_s^{(p)} + \sum_{p'=0}^{1} \sum_{s'=1}^{9} \sum_{t_i<t} \kappa_{ss'}^{(pp')}(t - t_i), \tag{1}$$

where the functional form of the triggering kernels is:

$$\kappa_{ss'}^{(pp')}(t) = \alpha_{ss'}^{(pp')} \omega^{(p)} e^{-\omega^{(p)} t}. \tag{2}$$

The parameter $\alpha_{ss'}^{(pp')}$ describes the excitation in intensity function of the process (s, p) as a result of an event occurring in spatial region s' of type p'.

The parameter $\omega^{(p)}$ describes the rate at which any excitation from prior events decreases. It can be interpreted as a characteristic time scale over which any increased risk due to a triggering event dissipates and, therefore, the time over which a triggered event (which is inspired by the first event) might be planned and carried out (Lewis et al., 2011).

The decay parameter $\omega^{(p)}$ for each process is fixed by event type for mathematical convenience in the calibration procedure and in order to aid interpretation of the spatial effects, which now only enter the model via the excitation parameter. Due to the functional form of equation 2, events with larger excitation parameters will take longer to return to baseline levels, even when the rate of decay is equal. This means that variation in both magnitude of excitation and the length of time taken to return to baseline levels is captured by the same excitation parameter. The excitation parameter handles all variation in the impact of different prior events on the intensity function.

The model in equations (1) and (2) is too general for practical calibration purposes: as it is specified, there are 18 background rates, 2 decay rates and $18^2 = 324$ excitation rates. Calibration of a model with so many parameters would likely be over-fitted. Thus, we place constraints on the parameters that we seek to calibrate. In what follows, we explain how the dimension of the parameter space is reduced for this purpose, resulting in models that are readily interpretable and which define interactions between the event data in different ways.

The first and simplest model we consider consists of just two parameters and can be specified by setting all excitation parameters $\alpha_{ss'}^{(pp')}$ equal to zero and by setting $\mu_s^{(p)} = \mu^{(p)}$ for all s, so that the background rate does not vary in space, but is allowed to vary between events that are exchanges of fire and events that do not involve police. This is a simple Poisson process with no spatial dependence and with two constant intensity functions: one for events involving police and one for events without police.

For the second model, we relax the constraint that there is no spatial dependence and obtain two different Poisson processes within each spatial region. Thus, 18 parameters are required to estimate a Poisson process for each event type within each of the nine spatial regions. Models 1 and 2 act as baselines against which the more complicated models described below will be compared.

The third model is a simple non-spatial Hawkes process for two event types, with and without police. This can be obtained from equations (1) and (2) by setting $\mu_s^{(p)} = \mu^{(p)}$ for all s and

$$\alpha_{ss'}^{(pp')} = \begin{cases} \alpha^{(p)} & \text{for } p = p' \\ 0 & \text{otherwise,} \end{cases}$$

so that events of type p, regardless of where they are located, cause the triggering kernel to increase the intensity of events of type p. Model 3 enables us to determine the extent of self-excitation in events of the same type and requires six parameters to be calibrated.

We also calibrate a local version of Model 3, so that events only trigger the intensity function for a particular district if they occur within that district. An improvement in the explanatory power of Model 4 over Model 3 would indicate that local triggering events matter more than events occurring elsewhere in the region, and, therefore, that local spatial processes are important to account for. This model can be obtained by setting

$$\alpha_{ss'}^{(pp')} = \begin{cases} \alpha^{(p)} & \text{for } p = p' \text{ and } s = s' \\ 0 & \text{otherwise.} \end{cases}$$

We define Model 4 with $\mu_s^{(p)} = \mu^{(p)}$, so that background rates do not vary with space (although, in this case, since the overall intensity function depends on a local triggering kernel, the intensity function will vary over space). Thus, we again require six parameters to be calibrated. Model 5 is defined similarly to Model 4, but with spatially varying background rates $\mu_s^{(p)}$, requiring 22 parameters.

Model 6 introduces the notion of mutual excitation, whereby an event involving police can trigger an event not involving police and vice versa. To specify this model, we set

$$\alpha_{ss'}^{(pp')} = \begin{cases} \alpha^{(pp')} & s = s' \\ 0 & \text{otherwise.} \end{cases}$$

Thus, four excitation parameters, $\alpha^{(00)}$, $\alpha^{(01)}$, $\alpha^{(10)}$ and $\alpha^{(11)}$ are calibrated, which capture the interaction between the different event types. These excitation parameters are defined locally, so that excitations only matter if events occur within the same district. In total, with two background rates and two decay rates for the two event types, eight parameters are required for calibration of model 6.

Finally, in Model 7, we define a model capable of capturing spatial effects. To do this, for each district s, we denote by $\mathcal{N}(s)$ the set of districts that share a border with s and we denote by $(\mathcal{N}(s) \cup s)^c$ the remaining set of non-neighboring districts. Then, for each district s, the effect from triggering events occurring in each of these sets of districts (i.e. s, $\mathcal{N}(s)$, and $(\mathcal{N}(s) \cup s)^c$) is modelled by an exponentially decaying triggering kernel with parameters that vary over each of the sets, but which are not dependent on s. In this way, we can capture excitations that occur locally, that occur across neighboring districts, and that occur across non-neighboring districts over the entire state and can compare their relative strengths. Thus, the final model is defined by setting

$$\alpha_{ss'}^{(pp')} = \begin{cases} \alpha_1^{(pp')} & s' = s \\ \alpha_2^{(pp')} & s' \in \mathcal{N}(s) \\ \alpha_3^{(pp')} & s' \in (\mathcal{N}(s) \cup s)^c. \end{cases} \tag{3}$$

Specifying different parameters for the possible values of p and p' in equation 3 (i.e. for $p, p' = 0, 1$), leads to 12 excitation parameters and 16 parameters in total to be calibrated.

Table 1 summarises the models whose parameters are calibrated using the calibration procedure described in the next section.

Table 1: Model list

Model 1:	Non-spatial Poisson
Model 2:	Spatial Poisson
Model 3:	Non-spatial self-excitation
Model 4:	Local self-excitation
Model 5:	Local self-excitation with spatial background rates
Model 6:	Local mutual excitation
Model 7:	Spatial mutual excitation

6. RESULTS

Table 2 presents the parameter estimates of models 1, 3, 4, 6 and 7 (i.e those which require 16 parameters or fewer), with associated standard errors. For ease of presentation, models 2 and 5 are not included in this table due to the large number of parameters associated with the spatially varying background rates. The detailed results are included in the supplementary materials accompanying this article. Although standard errors are reported, we do not report on p-values and associated statistical significance in Table 2. This is because the parameters are constrained by the model to remain non-negative, which creates non-normal distributions of parameters during the parametric bootstrap. These non-normal distributions mean that the normal p-value calculations do not apply[3].

Model 1 assumes that non-police events in each spatial region occur with a rate given by the constant $\mu^{(0)}$ and that police events in each spatial region occur with a rate given by $\mu^{(1)}$. This model resulted in the poorest fit to the data out of all the models tested. A spatially disaggregated Poisson process was calibrated as Model 2, consisting of 18 parameters, corresponding to the rates at which each type of event occurs in each of the 9 spatial regions under consideration. This model was estimated to assess if the performance of the model was improved when spatial heterogeneity is considered. For parsimony, this model is not reported in Table 1, but led to an improved model with an Akaike's Information Criterion (AIC) value of 23,842 (compared to 25,487 for the baseline model).

[3]Recent academic discussions have questioned the validity of an over-reliance on p-values and emphasise the importance of effect sizes (Nuzzo, 2014), which are reflected in the presentation of our results.

Table 2: Parameter and standard error (in parentheses) estimates for the models with non-spatial background rates. Parameters proceeded by the same dagger symbol for Model 3 are constrained to be equal in order to model the effect from events occurring over the entire state. Models 2 and 5 are omitted from the table due to their large number of parameters. They are included in the supplementary material accompanying this article.

			M1	M3	M4	M6	M7
Intensity of non-police events		Background rate	.0749	.0056	.0070	.0067	.0028
			(.0016)	(.0030)	(.0013)	(.0012)	(.0084)
	Self-excitation	Same district		.1029†	.9089	.8322	.7426
				(.0038)	(.0204)	(.0261)	(.0308)
		Neighbouring district		.1029†			.0384
				(.0038)			(.0107)
		Non-neighbouring district		.1029†			.0023
				(.0038)			(.0024)
	Mutual-excitation	Same district				.2990	.2874
						(.0738)	(.0782)
		Neighbouring district					.0000
							(.0180)
		Non-neighbouring district					.0011
							(.0047)
		Decay		.0767	.0312	.0364	.0478
				(.0112)	(.0027)	(.0032)	(.0055)
Intensity of police events		Background rate	.0202	.0030	.0025	.0006	.0000
			(.0008)	(.0012)	(.0008)	(.0005)	(.0032)
	Self-excitation	Same district		.0949‡	.8826	.3849	3548
				(.0066)	(.0461)	(.0489)	(.0568)
		Neighbouring district		.0949‡			.0088
				(.0066)			(.0089)
		Non-neighbouring district		.0949‡			.0067
				(.0066)			(.0056)
	Mutual excitation	Same district				.1590	.1500
						(.0143)	(.0166)
		Neighbouring district					.0025
							(.0029)
		Non-neighbouring district					.0000
							(.0010)
		Decay		.0499	.0114	.0218	.0258
				(.0095)	(.0018)	(.0034)	(.0056)
		Log likelihood	-12,742	-11,889	-10,929	-10,849	-10,817
		AIC	25,487	23,789	21,870	21,715	21,667

Model 3, corresponding to a self-exciting Hawkes process in which excitation of the intensity function occurs when an event of the same type happens anywhere across the entire state, shows a significant improvement on both the non-spatial Poisson process in Model 1 and on the spatially disaggregated Poisson process in Model 2, as can be seen by the lower AIC of 23,789. Therefore, a self-exciting Hawkes process appears to return a better model for explaining the variance in the data than both Model 1 and its spatially explicit alternative (Model 2). We interpret this as suggesting that the dominant mechanism explaining the observed variability is not spatial heterogeneity but rather the temporal clustering, as exhibited by a Hawkes process.

According to the parameters for Model 3, for each non-police event that occurs, the model predicts that, on average, a further 0.1029 non-police events will occur. For each police event that occurs, an average of 0.0949 further police events will occur. Three equal parameters for each excitation are reported in Table 2 to emphasise that the excitation occurs over the entire spatial region of interest regardless of whether the event occurs in the same district, a neighboring district, or a non-neighboring district (thus the three parameters are constrained to be equal to each other). The decay parameters, 0.0655 for non-police events and 0.0404 for police events, suggest that the excitation for non-police events decays more quickly back to baseline levels than for police events. Indeed, the characteristic time window over which the Naxals plan and carry out further attacks not involving police is 15 days, while those events involving police are likely to occur within 25 days of a triggering event.

Model 4 contains the same number of parameters as Model 3 but has a triggering kernel that only incorporates events that occur within the same district. This model is spatially explicit since the conditional intensity functions within each spatial region now vary from each other, depending on the number of events that occur in each district. A large improvement in model fit is observed, with the AIC reducing by nearly 10%. Furthermore, the excitation parameters estimated—0.9089 for non-police events and 0.8826 for events involving police—are much larger than the excitation parameters in Model 3. The model predicts that, for each event that occurs, nearly one further event of the same type will occur in the same spatial region. The decay parameters suggest that for non-police events, this further event will occur in the month following an event, whilst for events involving police, this extra event may take up to three months to occur. The large improvement in model fit when excitation acts locally lends support to hypotheses concerning spatio-temporal clustering: events are more likely to occur in the aftermath of a prior event, particularly in close spatial proximity to that prior event.

A multi-level version of Model 4 was also estimated (Model 5) but is not reported here. This model was estimated to test whether the inclusion of spatially varying background rates significantly altered the results. If the resulting parameter estimates were significantly different from those reported in Table 2, then it may be that, rather than capturing the excitation effects due to the occurrence of events, the model is actually capturing (time-stable) spatial heterogeneity. The parameter estimates for the triggering kernel in the multilevel model—which were not made spatially explicit—were consistent with those reported in Table 2. The AIC value for the multi-level model was 21,836 and, thus, the decrease in the AIC value from Model 4 was the smallest reduction of all the models tested in this article. As a consequence, and in order to perform out of sample testing of the model in what follows, models with constant background rates over the spatial region of interest are preferred.

Model 6 incorporates interacting excitation effects between different event types within the same spatial region. The excitation of the non-police intensity function due to the occurrence of local police events and the excitation of the police intensity function due to the occurrence of local non-police events are both greater than zero with relatively small standard errors, indicative of an interaction effect. For each police event that occurs, this model predicts an average of 0.2990 further non-police events and, for each non-police event, an average of 0.1590 police events are predicted. In comparison to Model 4, the self-excitation rates are reduced to 0.8322 and 0.3849 for non-police and police events respectively, suggesting that some of the excitation found in Model 4 can be better explained by interaction effects. Indeed, the AIC for Model 5 is lower than that found for Model 4, suggesting an improved model.

Model 7, which introduces excitation effects from events occurring in neighboring and non-neighboring districts, further improves model fit, as indicated by the lower AIC value. In addition, the estimated parameter values provide support for the hypothesis that the impact of prior events decays as events occur farther from the region of interest. That is, for events of both types, self-excitation is strongest in the district within which the events take place and weakens by an order of magnitude for events occurring in neighboring districts, before reducing to a negligible effect for events that occur elsewhere in Telangana. For police events, however, the self-excitation effect from neighboring and non-neighboring districts is associated with large standard errors. Mutual excitation across different spatial regions is negligible for both event types.

As a further test of model validity, and to additionally determine whether the models might of use in a policy setting, we also undertook an out of sample prediction test for each model. For this task, each model was used to classify whether, given the history of the system up until the start of each day, an attack either involving police or not would occur. The model for each spatial region was calibrated using all events outside of that region and tested in each region. The results (provided in supplementary material) show that all models are capable of modest predictive performance and that the predictive capability increases with increasing model complexity. These results demonstrate that such models might be put to use as a tool to help plan police resources and responses to insurgent activity.

7. INTERPRETATION AND IMPLICATIONS FOR POLICING

The results presented in Table 2 highlight a number of important implications for policing. Our findings suggest that incidents of Naxal violence are not independent. Instead, when an event occurs, the risk of additional incidents is temporarily elevated. This elevated risk also applies to events involving exchanges of fire between Naxals and police. This finding is in line with those of studies that have examined insurgencies in other countries—including Iraq (Lewis et al., 2011), Israel (Mohler, 2013), Indonesia (Porter and White, 2012) and Northern Ireland (Tench et al., 2016)—suggesting that this may be a general characteristic of insurgency. Our results support our first hypothesis: events are temporally clustered, regardless of whether police are present or not.

Comparing the self-excitation mechanism between police and non-police events, for example in Models 3 and 4, we see that each event is estimated to trigger a very similar number of further events (around 0.1 in Model 3 and 0.9 in Model 4). We find, however, that excitation associated with police events decays more slowly than excitation associated with non-police events. That is, the impact from exchanges of fire on the system has a longer duration than the impact from non-police events. Although exchanges of fire do not necessarily generate more triggered events, they do appear to have greater prominence in the memory of both Naxals and police.

The elevated risk of events occurring following violent attacks and exchanges of fire is much more prominent within the district in which those events actually occurred, suggesting that geographic concentration of events plays an important role at the levels of analysis employed. Following a violent outburst in one part of the state, it may be a waste of resources to put all police forces within the state on high alert. Instead, it is those police who are geographically proximate to the outburst of violence who should be most aware of the elevation in risk. However, although the greatest influence is on events within the same district, we also find that events that occur in one district appear to influence the risk of events in neighboring ones (albeit to a lesser extent). A number of previous studies have found similar evidence for the spreading and escalation of violence across geographic units of analysis during insurgencies (Schutte and Weidmann, 2011; O'Loughlin and Witmer, 2012). These same patterns emerge for exchanges of fire, although the rate of diffusion is slower and more uncertain. Large standard errors when considering the influence from non-neighboring districts suggests that there is a limit to the spatial extent of the influence from prior events. Consequently, we find evidence for spatial decay. The influence from prior events decays with the distance from those events, supporting our second hypothesis.

There is also evidence of mutual excitation, whereby the likelihood of a Naxal attack increases following exchanges of fire with police and vice-versa. This finding is in agreement with a tit-for-tat process between the two sides of the conflict, a finding that has been observed elsewhere for other conflicts (Haushofer et al., 2010; Linke et al., 2012). Following exchanges of fire, Naxals are more likely to engage in further violent events themselves. Engagement with counterinsurgents therefore appears to make the Naxals more willing to conduct violent attacks, at least in the short term. Consequently, police presence appears to exacerbate the conflict, supporting our third hypothesis. Further research might seek to determine whether this finding is a result of increased Naxal grievances following a counterinsurgent attack; whether it is due to the Naxals themselves being buoyed by damaging the resources and resolve of the police; or whether there is some unobserved role played by civilians, whereby Naxals seek to re-establish their reputation amongst civilians, in spite of possible recent setbacks.

Finally, assuming that a significant number of exchanges of fire events were the result of counterinsurgent operations, the police appear to respond to a period of heightened Naxal activity. In fact, almost all the dynamics for police events in Models 6 and 7 are estimated to be the result of excitation, rather than from background events. These results support our final hypothesis: crime events increase the likelihood of future events with a police presence for a short period of time.

8. CONCLUSION

We have calibrated a number of multivariate Hawkes process models on data associated with insurgent activity—and police interaction with such activity—at a local level of analysis. Our results suggest that: 1) the phenomenon of spatio-temporal clustering is present in the Naxal conflict; 2) police presence at crime events exacerbated the conflict, leading to more events than would have otherwise occurred, at least in the short term; and 3) the space-time regularities can be usefully employed to predict the likely locations of future events.

Despite these important insights, there are some limitations associated with the models presented. First, the data are necessarily aggregated to rather large spatial units (districts). Greater insight might be obtained by a more finely-grained analysis in space. Our choice of units, however, was guided by information obtained by the Indian Police Service, and was chosen to correspond to units over which police routinely make deployment decisions. Second, it is plausible that our current analyzes suffer from endogeneity in the data generating processes being modeled. The precise direction of causality between non-police events and police events is plausibly more complicated than we have been able to capture in the current study. Despite this, we have shown that our modeling procedure captures important spatio-temporal regularities, as evidenced by a modest amount of predictive capability. Third, the data was aggregated so that each type of event (and police encounter) was counted equally, regardless of what it was. Naxal attacks vary in nature from threats, to shootings, to IED attacks and hence may differ in the extent to which they encourage insurgent or police action. Thus, future work might examine if the predictive accuracy of models can be improved by taking account of the severity, or other characteristics of attacks.

Our findings suggest that such models might usefully be employed in an operational setting to help police deployment decisions. Unsurprisingly, our results indicate a gradual improvement in predictive capability as the complexity of the model is increased. It may be that the inclusion of additional variables (such as population density, deprivation, or the locations of known insurgent strongholds) might further improve predictive performance. Nevertheless, our findings have provided important insights into the Naxal insurgency and the police response. In addition to demonstrating the power of a parsimonious model specification, we have demonstrated the vulnerability of locations to further attacks at the same location and those nearby. This kind of conclusion arguably provides actionable intelligence to those agencies charged with managing non-state actor violence.

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