Modeling Dynamic Violence: Integrating Events Data Analysis and Agent-Based Modeling[1]

Michael G. Findley[2]
Department of Government, University of Texas at Austin

Stephen Shellman
Institute for the Theory and Practice of IR, College of William & Mary

Joseph K. Young
School of Public Affairs, American University

Andreas Beger
Department of Political Science, Florida State University

Abstract

Which actions by governments stoke or pacify an insurgency? Scholarly research on the topic has often been relegated to the country level, comparing across large units and rarely looking inside the state. Our research focuses on the primary actors in a contest for authority within a state: the government, dissidents, and the population. In contrast to extant subnational work, we address the difficult question of how population dynamics affect the rise and fall of insurgency. We investigate the question in the context of India and its subnational administrative districts. India is particularly well suited to this research as it presently experiences varying levels of terrorism, insurgency, ethnic conflict, riots and other actions that threaten the stability of the state. Using an agent-based model (ABM), geographic information systems (GIS), data on public sentiment, and events data, we address this question from a multidisciplinary approach. The agent-based model formalizes the interactions of states, dissidents, and the population, the GIS framework allows for actual demographic and geographic information to influence this interaction, and the events data and sentiment data allow us to test empirical implications from the model directly. We expect the results to have important implications for the study of political violence, order, and state-building. The approach is policy relevant, furthermore, and can be adapted to other regions and countries.

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Introduction

The US and its Coalition partners invaded Afghanistan in October of 2001 thus beginning a conflict that still continues today. The first phase of the conflict for the US involved partnering with Britain, other external allies, and with the Northern Alliance, a local insurgency that challenged the ruling Taliban. After ousting the Taliban, the US and its allies helped set up a democratic regime. The conflict then shifted into a new phase characterized by counterinsurgency against the remnants of the Taliban regime and its allies, which began in 2002 and continues to this day. Violence levels have varied a great deal over the course of the conflict with a recent upsurge in civilian and US deaths. Since 2002, a key question continues to permeate all military and political discussions and decisions: which actions by the US or the Afghan government encourage or discourage violence by insurgents?

This question represents one of the most enduring problems plaguing governments faced by violent opposition movements. From Vietnam to Iraq, the U.S. has grappled with this question. Numerous other governments – India, Philippines, Colombia, Algeria, Sierra Leone, Israel, Russia, for examples – face similar pressure within the boundaries of their own state. As these examples suggest, modern insurgency ebbs and flows over time within conflict zones. We seek to understand more generally, which actions by governments stoke or pacify an insurgency.

Although much attention has been paid to these questions – by the military, policymakers, and scholars – in this paper we offer a unique approach. First, we place the role of members of a population central to understanding the dynamics of insurgency. As Mao Zedong (2005, 93) argued in his classic treatise on guerrilla conflict, the guerrilla must move among the population as a fish swims in the sea. In Mao's terms, most studies of

insurgency have examined the fish while ignoring the sea, whereas we consider how a localized, heterogeneous population affects, and is affected by, insurgents and counterinsurgents.[3] Second, we use methodologies better suited for addressing the complexities of insurgency. In the study of insurgency, a wide variety of moving parts complicate the isolation of causal relationships. Randomized experiments represent the gold standard for teasing out cause and effect, but such experiments in the context of insurgency and counterinsurgency are difficult, at best. We instead design and implement a computational model of the interaction among the population, insurgents, and counterinsurgents that allows a virtual laboratory in which we can incrementally change features of the model and then "rerun history" many different ways. Third, we test predictions from the model using original events data that incorporate actions and beliefs among the three central actors: insurgents, counterinsurgents, and the population. Most notably, we attempt to match new empirical data that capture the beliefs (sentiment) and actions of the population towards insurgents and counterinsurgents with the computational model.

We begin by reviewing prominent academic and military literature on insurgency, with an emphasis on work that considers the role of the population, in addition to insurgents and counterinsurgents. Drawing on substantive theory, we then develop a computational model to capture key elements of the environment, actors, and behaviors (Pepinsky 2005) of insurgency. We then identify the key concepts and outcomes in the computational model and test them using "sentiment" data.[4] In particular, we discuss how we extracted data from

[3] Siqueira and Sandler (2006) is a notable exception of a model that also includes the population in a study of the interaction between the state and dissidents, although even it resorts to simplifying assumptions that make the population a homogenous actor.

[4] It is most common for a formal algebraic model to be paired with statistical tests of the comparative statics of the model (See, for example, Drakos and Kutan (2004) and Mukherjee (2006)). Although an Empirical

the interaction of the state, dissidents, and the population in India during the period 1998 to 2008 and present some initial empirical results. The research is currently midstream, but the initial results suggest that violent insurgent and counterinsurgent strategies make the population less likely to support the actor using violence. Thus, approaches designed to win the hearts and minds of the people appear to be more viable long-term strategies. We conclude with a discussion of how this approach can be applied to other countries, regions, and topical areas.

The Multidisciplinary Study of Insurgency

To understand insurgency, academics and tacticians have often considered the role of insurgents, the state, or their interaction. Although insurgency, per se, is an understudied topic among academics, much academic work focuses on the causes, duration, or resolution of the most extreme form of insurgency – civil war (e.g., Collier and Hoeffler 2004, Fearon and Laitin 2003, Collier, Hoeffler, and Soderberg, 2004, DeRouen and Sobek 2004, Cunningham 2006, Walter 1997, 1999). Often civil war is conceptualized as a violent contention between the state and insurgent groups where both sides participate in killing and the death toll exceeds 1,000 battle deaths.[5] Inherent in this definition is the violent interaction of states and dissidents/insurgents, but few studies explicitly model this

Implications of Theoretical Models (EITM) approach, or a formal model tested using quantitative analysis, has become more common in economics and political science (Granato and Scioli 2004) it has rarely been attempted using a formal computational model paired with statistical analysis.

[5] See Sambanis (2004) for a thorough discussion of the ways to conceptualize and operationalize civil war along with the pitfalls of different approaches.

interaction (Young 2008); even more problematic, few studies consider how the population influences these outcomes.[6,7]

Understanding how states resolve insurgencies requires an understanding of the populations affected by this violence. David Galula, the French military officer and counterinsurgency (COIN) theorist, suggests this is the case. Galula's (1964, 74-75) first law of COIN states that the struggle between the insurgents and the government is over the support of the population rather than territory.[8]

Within the academic literature, Weinstein (2007) and Kalyvas (2006) are the most prominent examples of recent attempts to understand the dynamics of insurgency while focusing on the role of the population. Each has a compelling and straightforward explanation for the use of violence in insurgent conflicts. Both rely on structural factors that explain killings in civil conflicts, which are highly correlated with the length of an insurgency. Focusing solely on rebel groups, Weinstein (2007) suggests that initial resource endowments explain why insurgents kill indiscriminately. He argues that where insurgents rely on the population for resources, they are less likely to kill. Weinstein's theory is elegant in its simplicity but does not take into account what the state is doing when explaining insurgent violence. While Weinstein can help us understand why insurgents may or may not use indiscriminate violence, it cannot tell us much about the strategic interaction between the state and insurgents. For Kalyvas (1999, 2006), the use of selective and indiscriminate violence is related to territorial control. His theory offers an explanation for where these

[6] We use the term dissident to refer to an individual who uses non-institutional means to challenge the state and its policies. An insurgent uses violent means. All insurgents are thus dissidents but not all dissidents are insurgents.
[7] Shellman (2006a, 2006b) and Moore (1998, 2000) are important exceptions, though they do not explicitly discuss civil war.
[8] Trinquier (1961), another former French military officer, argued after fighting in Indochina and Algeria that central tenet of COIN was winning the allegiance of the indigenous population.

types of violence should occur and whether the government or insurgents is more likely to commit these acts. In short, we should expect selective violence where either insurgents or the government exercises predominant authority but not complete control. Areas completely controlled by one side or the other should be devoid of violence by the incumbent but should expect to see indiscriminate violence from the party that lacks control. Kalyvas' work is unique as it places control over the population at the center of the insurgent/counterinsurgent conflict and offers hypotheses about when, where, and what type of violence each side will use during the conflict. While Kalyvas strategic theory is an improvement on more static arguments, it cannot explain how heterogeneous populations influence this process. For Kalyvas, support for the insurgents or counterinsurgents relates to control rather than ideology, commitment, or belief.

Counterinsurgency and the Military

Military theorists and academics who study insurgency have made complementary claims. Galula (1964), for example, argued for a strategy of dividing conflicts into three different zones depending on which side controls the territory (red-insurgents, pink-mixed, white-counterinsurgents). For Galula (1964), a successful counterinsurgency strategy attempts to hold the white areas and use them as a base to target the pink areas and turn them white. Then, the task is to make the red areas pink and so on. Galula (1964, 63) argues, quoting Mao that, "revolutionary war is 80 percent political action and only 20 percent military." This suggests an integrated approach, which includes diplomatic, informational, military, and economic means to gain the support of the population. Galula's ideas were prominently cited in the recent US Army Counterinsurgency manual authored by John Nagl and General

David Petraeus, which focuses on the battle for support of members of the population (hearts and minds), rather than a war of attrition.

In contrast, in the 1970s during the height of the Vietnam conflict, Leites and Wolf (1970) argued that winning a conflict with an insurgency required raising the costs associated with participating in violence against the state and its interests. For Leites and Wolf (1970) rational people would be dissuaded from helping or participating in violence by the extreme costs inflicted upon them by counterinsurgents.[9] The experiences of the US military in Vietnam seemed to discredit this approach (Bulloch 1996), but the US experience with counterinsurgency against the Native Americans seemed to support these ideas. In the current global context generating tremendous costs for populations associated with insurgencies may or may not work, but they could also have dramatic effects on the stature of the state in the international system. Emerging human rights norms and commitments to democracy are clearly at odds with this form of counterinsurgency.

In the next section, we outline a test of whether a benefit-centered (hearts and minds) or cost-centered (attrition) approach is better at reducing the strength of insurgency. We develop a computational model to approximate an experiment in which different parameters, such as the support of the population, insurgent, or counterinsurgent strategies, and many other factors, can be adjusted to explore whether they influence the number of insurgents and, thus, the strength of the insurgency.

[9] This approach is sometimes referred to as "attrition" (Bulloch 1996, Findley and Young 2007).

Computational Model

Computational models vary in their complexity, ranging from simple cellular automata simulations (Wolfram 1984) to complex models of single political systems (Cioffi-Revilla and Rouleau 2010) to world simulations with massive numbers of parameters (Prinn et al. 1999). No one formula is correct and, arguably, a model's complexity should be a function of the substantive problem at hand (Lustick and Miodownik 2007). Computational models of insurgent violence have only recently begun to become more common (e.g., Bennett 2008, Bhavnani and Backer 2000, Bhavnani 2006, Cederman 2004, Epstein 2002, Findley 2008, Findley and Young 2007, Kuran 1991, Luke et al. 2005). Our computational model attempts to strike a balance between capturing realistic aspects of insurgent violence through the incorporation of GIS (Cederman and Girardin 2007) while limiting the complexity of the model to a manageable number of parameters (de Marchi 2005). The model shares much in common with Epstein (2002) and Findley and Young (2007), but extends these models in ways that allow a better understanding of the dynamics of insurgency.

The Environment

Our model builds from others who model dynamics on an explicit spatial landscape (e.g., Epstein 2002; Findley and Young 2007; Schelling 1978), but we blend actual GIS data of country and sub-national administrative boundaries with a model comprised of artificial agents (Brown, et al 2005). Thus, a GIS representation of countries and subnational administrative districts, as opposed to an imposed landscape such as a grid or torus, represents the topography on which agents interact. The platform supports modeling

insurgency and violence in 25 Southeast Asian countries; we begin in this paper with the case of India, modeling the entire country as well as the Jammu and Kashmir region only.

The boundaries of the simulation are based on the boundaries of the country of India or of various administrative districts (e.g., states and union territories) within India. From that point, the map is divided into a synthetic grid of approximately 100 equal-sized "zones of control", which track the overall level of perceived rebel control within broad portions of the geography. Each zone is given a label from 1-5 depending on the level of insurgent control within that zone, calculated as number of insurgents divided by number of insurgents and counterinsurgents within that zone. The zone labels correspond to 20% increments of insurgent control, from 0 to 100%. GIS data on factors such as ethnicity and population density are currently built into the model, and a number of other GIS characteristics are in progress, and we report results for Jammu and Kashmir in which the distribution of agents matches the region's demographics. We discuss agent mobility below, but first turn to a specification of the agents. Table 1 lists the notation and parameters of the model along with short descriptions.

[Table 1 Here][10]

Agents

Three primary types of agents exist in the model: Population/Civilian: α_i^{π}; Counterinsurgent: α_i^{κ}; Insurgent: α_i^{λ}. Civilians are further divided based on their allegiance to the two factions: Insurgent collaborators τ^{λ}, Counterinsurgent collaborators τ^{κ}, and indifferent civilians τ^{π}, where $\tau^{\lambda}, \tau^{\kappa}, \tau^{\pi} \subset \alpha^{\pi}$. The relative size of each group of agents is initially determined

[10] For the sake of keeping notation consistent, attributes which pertain to and vary between individual agents will use Greek lettering, and parameters which apply globally to the entire model will use Roman characters.

exogenously. Following Lichbach (1995), the population is the largest group comprised of roughly 85% of the agents; the counterinsurgents represent the next most populous group with 10% of the agents and the insurgents represent the remaining 5%.[11] Each agent has the attributes which compose the n-tuple: $\alpha_i \in \{\chi_i, \omega_i, \mu_i, \beta_i, \gamma_i, \upsilon_i, \delta_i, \rho_i, \sigma_i, \phi_i\}$, which we now explain:

Commitment, χ_i*:* An agent's commitment to the insurgency ranges over the unit interval, [0,1], where the higher the value, the higher the agent's commitment to the insurgency. We begin with the assumption that the population is inclined to be neutral and support whichever side appears to be winning (Krepinevich 2004). Thus, commitment is initially distributed to all agents according to an approximated Pearson distribution described by a *shape* parameter S, hereafter labeled *skewness*, which allows the generation of population distributions skewed by a specified amount towards the counterinsurgents (right) and the insurgents (left). When $S = 0$, the distribution is that of a standard normal curve. The actual equation used for the distribution is $t(x) = e^{\frac{-S*\tan^{-1}(x-0.7*S)}{(1+(x-0.7*S)^2)^2}}$. From this distribution, insurgent and counterinsurgent *commitment bounds* $\theta^{\lambda}$and $\theta^{\kappa}$are calculated such that $\int_{-\infty}^{\theta^{\kappa}} dist(\mathrm{x})\mathrm{dx} = \widehat{\alpha}^{\kappa}$, and $\int_{\theta^{\lambda}}^{\infty} dist(\mathrm{x})\mathrm{dx} = \widehat{\alpha}^{\lambda}$ (where $\widehat{\alpha}^{\kappa}$ and $\widehat{\alpha}^{\lambda}$ are the desired proportions of counterinsurgents and insurgents relative to the entire population, set by parameter). In addition, insurgent and counterinsurgent *collaboration thresholds* ψ^{λ} and ψ^{κ} are calculated such that $\int_{-\infty}^{\psi^{\kappa}} dist(\mathrm{x})\mathrm{dx} = \widehat{\alpha}^{\kappa} + \left(1 - \widehat{\alpha}^{\kappa} - \widehat{\alpha}^{\lambda}\right) * 0.33$ and $\int_{\psi^{\lambda}}^{\infty} dist(\mathrm{x})\mathrm{dx} = \widehat{\alpha}^{\lambda} + \left(1 - \widehat{\alpha}^{\kappa} - \widehat{\alpha}^{\lambda}\right) * 0.33$. These equations ensure that, regardless of the shape of the commitment distribution, the area of the tail on the left equals the percentage of counterinsurgents, and the area of the tail on the

[11] Group size is parameterized and can be altered to explore different configurations.

right equals the percentage of insurgents. From the remaining area that is left in the middle (composing civilian commitments), the lower third will become counterinsurgent collaborators, and the upper third will become insurgent collaborators. While generating commitments for newly created agents, commitment levels that fall below θ^{κ} will lead to the generation of a counterinsurgent, levels above θ^{λ} will generate an insurgent, and all other commitments will generate a civilian. In the case of civilians, those with commitments below ψ^{κ} become counterinsurgent collaborators, and those above ψ^{λ} become insurgent collaborators. Each agent's commitment is updated throughout the simulation based on interactions with other agents.

Responsiveness, ω_i*:* Agents are heterogeneous in their propensity to change their commitment to the insurgency. Responsiveness represents something of an elasticity in which some agents might update their commitment in only very small increments while others might update in larger increments (Findley and Young 2007). ω_i is drawn from a uniform distribution $U(0, R)$, where *R* is the maximum responsiveness of an agent, set by parameter. Once assigned, responsiveness never changes for an agent.[12]

Belief Radius, μ_i: The belief radius determines the distance at which an agent's belief can be influenced by its nearest neighbors. The belief radius for all agents is calculated automatically at the beginning of the simulation and is fixed for all agents throughout their lifetime. Since the belief radius correlates so much to an agent's local zone of control, the radius is calculated to be the minimum size required to encompass a single zone. Given that each zone is approximately square, this radius is the circle which inscribes that square, therefore

[12] This could be parameterized, of course, to allow for an endogenous level of responsiveness to insurgent or counterinsurgent actions.

$\mu_i = zone\ size * \sqrt{2}$, where *zone size* is the larger of either the width or height of a single zone of control.

Beliefs, β_i: Given the decentralized character of insurgencies, no one agent has complete information (Clausewitz 1976; Epstein 2002; Hayek 1945). Agents, in this model, are therefore heterogeneous in their beliefs about the strength of the overall insurgency. Initial belief is initialized exogenously, but then an agent's belief is updated at each time step according to the type of agents within a local region. This is done by adding up the number of all types of agents within the belief radius μ_i, and letting $\beta_i = \frac{\alpha^\lambda + \frac{\tau^\lambda}{2}}{(\alpha^\lambda + \frac{\tau^\lambda}{2}) + (\alpha^\kappa + \frac{\tau^\kappa}{2})}$ (In other words, number of insurgents plus half the number of insurgent collaborators, divided by the same plus the number of counterinsurgents and half the number of counterinsurgent collaborators).

Move distance, γ_i: The move distance for all agents is calculated automatically at the beginning of the simulation according to the size of the geography, and is fixed for all agents throughout their lifetime. The equation to calculate this value is $\gamma_i = {size}/{M}$, where *size* is either the width or height of the entire model geography (whichever is larger), and *M* is a global parameter (300 by default).

Interact radius, υ_i: This defines the maximum distance that agents can interact with others around them. Like move distance, this value is calculated automatically and fixed for all agents for the entire simulation, according to the equation $\upsilon_i = {size}/{F}$, where *size* is the country size defined above, and *F* is a global parameter (50 by default).

Discipline, δ_i*:* A value from 0.0 to 1.0, this defines an agent's propensity to give economic benefits rather than costs – a discipline of 0.8, for example, would describe an agent which will give benefits in 80% of its economic interactions. After every interaction, an agent's discipline will increase slightly if it gave benefits, and decrease slightly if it imposed costs.

Resources, ρ_i*:* This represents the fixed resource endowment that is available to the agent's faction, ranging from 0.0 to 1.0, and influences the strategies that a faction will employ while attempting to recruit others to their cause.

Capacity, σ_i*:* Determines an agent's ability to assassinate denounced enemy collaborators, expressed as a probability from 0.0 to 1.0. Also correlates to the perceived offensive strength of that agent's faction. This value can differ between insurgents and counterinsurgents, but all agents within one faction will have the same capacity.

Vision, ϕ_i*:* Given that agents have little detailed information about rebel activity, their perception of the strength of each faction is determined only by the perceived level of insurgent or counterinsurgent control in nearby geographic zones of control. Thus, ϕ_i defines the size of a Von Neumann neighborhood, at which agents can inspect zones of control neighboring the one they are currently in while making decisions. This attribute may have a different value depending on whether the agent is an insurgent or a counterinsurgent.

Upon model initialization, all of the zones of control are assigned random labels from 1-5. *N* agents are then randomly assigned an initial location within the specified geographic boundaries, while maintaining a ratio of insurgents and counterinsurgents within these zones which correspond to their labels (where label = 1 corresponds to 0-20% insurgent control, label = 2 corresponds to 20-40% insurgent control, etc.). The level of "insurgent control" in

each zone is determined by number of insurgents divided by number of political actors within the zone. After agents are initially placed, the zone labels are no longer fixed, but are determined by the actual ratio of insurgents/counterinsurgents within that zone.

After the model is initialized, it proceeds in an iterative three-step process: agents (1) move about spatially, (2) interact with other agents, and (3) update their beliefs. Each type of agent performs at least some of these tasks, but agents may carry them out differently. We now consider the rules governing mobility, interaction, and belief updating.

Mobility

During the move phase, each civilian (α_i^{π}) is randomly assigned a trajectory in degrees between 0 and 360. The civilian then attempts to move in that direction.[13] Insurgents (α_i^{λ}) will wander within their current zone and attempt to interact with nearby civilians. Similar to Epstein (2002), vision is limited and all information is localized. Therefore, insurgents will monitor the level of counterinsurgent presence within their local zone of control (determined by $\frac{\alpha^{\lambda}+\frac{\tau^{\lambda}}{2}}{\alpha^{\pi}}$, or in other words, the number of counterinsurgents plus half the number of counterinsurgent collaborators, divided by the number of civilians). If the counterinsurgent presence within their zone is greater than the global parameter *D* (0.5 by default), insurgents will move to the nearest adjacent zone within their vision (ϕ_i^{λ}) with counterinsurgent presence of less than *D*.

Every time a counterinsurgent (α_i^{κ}) moves, it inspects all zones of control within a Von Neumann neighborhood of size = ϕ_i^{κ} from itself, and advances towards the closest zone

[13] Agents are not allowed to cross the outer boundary of the simulation. If the agent is randomly assigned a direction that will take it outside of the boundaries, it undoes its previous movement and tries again until it is successful.

where insurgent presence (defined as $\frac{\alpha^{\lambda}+\frac{\tau^{\lambda}}{2}}{\alpha^{\pi}}$ - that is, the number of insurgents plus half the number of insurgent collaborators, divided by total number of civilians) is greater than the parameter *H* (0.25 by default). If the insurgent presence in the agent's current zone satisfies this, he will wander within that zone. If no zones within ϕ_i^{κ} satisfy this, the insurgents are considered "concealed", and the agent will move randomly. Insurgents and counterinsurgents will attempt to influence civilians to be more committed to their own side, and target denounced enemy collaborators to assassinate them, which we discuss below.

Interaction

In contrast to Epstein's (2002) model, in which the key dynamic is whether agents choose to rebel, in our model insurgents and counterinsurgents employ strategies to win over the population. These strategies are divided into two types: *social* and *economic* interactions. In economic interactions, both insurgents and counterinsurgents exchange benefits - representing basic economic improvements, security, and freedom from previous abuses (Shafer 1988; Heath, et al 2000), and costs - capturing activities such as repression, torture, intrusive searches, or abuses and crimes by the military (Leites and Wolf 1970). In social interactions, agents either succeed or fail in their attempt to sway others on the grounds of shared beliefs, ethnicity, ideology, and cultural norms (Weinstein 2007). Beginning with civilians, we consider the different possible interactions among the agents.

Civilians: Civilians' primary role in the model is to receive costs and benefits from the opposing factions, and, when appropriate, collaborate with those political agents in denouncing other enemy collaborators. Intuitively, when civilians receive benefits they adjust

their commitment closer to the commitment level of the agent that gave them benefits. The overall effect of a single interaction is determined by the civilian's individual responsiveness (ω_i) and discipline (δ_i) attributes, as well as the type of interaction that it is (economic or social):

$$\Delta\chi_i = \begin{cases} \omega_i * \delta_i \text{ (for social interactions)} \\ \omega_i * (1 - \delta_i) \text{ (for economic interactions)} \end{cases}$$

This rule makes agents with high discipline more responsive to social interactions, and agents with low discipline more responsive to economic interactions. This attempts to model different recruitment strategies as groups attempt to attract highly committed individuals to their cause. Immediate economic rewards will tend to attract undisciplined "consumers", while ideological appeals and promises of freedom from grievance will attract more disciplined "investors" (Weinstein 2007).

Civilians with a commitment level less than the counterinsurgent collaboration threshold ψ^{κ} are considered counterinsurgent collaborators (τ^{κ}). Likewise, those with commitments greater than ψ^{λ} are considered insurgent collaborators (τ^{λ}). If the civilian is a collaborator for one political faction (either insurgent or counterinsurgent), they will attempt to *denounce* the nearest agent during their interact phase. If the nearest agent is either a collaborator for or a member of the enemy faction, the civilian will denounce the other if the *utility of denunciation* is above a certain threshold *T*, set by parameter. The benefit of denunciation is determined by the resources, $\rho^{\lambda,\kappa}$, which can be promised by the friendly faction as a reward, and the belief β in the local strength of that faction. The equation is:

$$benefit(denounce) = \begin{cases} \rho^{\lambda} * \beta_i \ (for\ insurgents) \\ \rho^{\kappa} * (1 - \beta_i) \ (for\ counterinsurgents) \end{cases}$$

The cost of denunciation is determined by the agent's commitment to his own faction χ_i, his belief in the local strength of the enemy faction $(1-\beta_i)$, and the capacity of the enemy faction σ, as so:

$$cost(denounce) = \begin{cases} (1-\chi_i) * (1-\beta_i) * \sigma^{\kappa} \ (for\ insurgents) \\ \chi_i * \beta_i * \sigma^{\lambda} \ (for\ counterinsurgents) \end{cases}$$

These equations give utility of denunciation determined by the equation:

$$utility(denounce) = \begin{cases} \left(\rho^{\lambda} * \beta_i\right) - ((1-\chi_i) * (1-\beta_i) * \sigma^{\kappa}) \ (for\ insurgents) \\ (\rho^{\kappa} * (1-\beta_i)) - (\chi_i * \beta_i * \sigma^{\lambda}) \ (for\ counterinsurgents) \end{cases}$$

Insurgents: Once an insurgent moves within distance of another agent, the insurgent initiates an interaction in which it gives costs or benefits. Insurgents can only give costs or benefits to civilians. The insurgency's *resource attribute* (ρ^{λ}) determines if the agent will attempt a *social* or an *economic* interaction. Higher resource endowment for a faction will directly correlate to a higher probability of economic interaction (where 0.0 = never, 1.0 = always). For economic interactions, the discipline characteristic of the agent initiating the interaction determines the probability that that agent will give costs or benefits. For example, a discipline of 0.7 would mean a 70% chance of giving benefits in this interaction. For social interactions, the current *popularity* of the insurgents is used as the probability that the social appeal will be effective. The popularity of the insurgency is determined by the number of interactions by insurgents in the last E time-steps in which insurgents gave benefits, divided by the total number of positive and negative interactions in that timeframe. In addition to this, the probability of the social appeal being successful is augmented by the insurgency's overall *social advantage*, A^{λ}, set by parameter. This value is added to the popularity to obtain the true probability of a

successful social appeal – for example, $A^{\lambda} = 0.1$ would correlate to a constant 10% increased chance of a positive interaction.

After costs or benefits are applied, agents update their commitment as described above. If the agent is a denounced collaborator for the enemy faction, then the insurgent will also at this time attempt to assassinate him with *capacity* σ^{λ}, set by parameter. σ^{λ} is the probability of successfully assassinating the collaborator – if success, the target is immediately removed from the simulation, and a new agent is spawned elsewhere to keep the population constant; if failure, the target's "denounced" status is immediately lifted.

Counterinsurgents: After moving, a counterinsurgent interacts with the closest civilian or insurgent within its neighbor radius. Like insurgents, counterinsurgents choose between playing costs and benefits, as well as take part in neutralizing enemy collaborators. Unlike insurgents, they can interact with both civilians and insurgents indiscriminately. The choice between costs and benefits is made in exactly the same way that it is made for insurgents, though using the counterinsurgent attributes for resources, discipline, popularity, and capacity.

Belief Updating

As alluded to above, the decision to denounce enemy agents is partly based on insurgent and counterinsurgent beliefs about the strength of the insurgency. After each move, insurgents and counterinsurgents update their beliefs according to the number of different types of other agents within this agent's belief radius, using the equation described earlier: $\beta_i = \frac{\alpha^{\lambda}+\frac{\tau^{\lambda}}{2}}{(\alpha^{\lambda}+\frac{\tau^{\lambda}}{2})+(\alpha^{\kappa}+\frac{\tau^{\kappa}}{2})}$.

Initial Experimental Strategy

In this initial exercise, we will primarily vary the initial discipline of both the insurgent and counterinsurgent groups, along with the initial population commitment or sentiment towards the insurgency (commitment skewness). These initial values are, of course, weighted by repeatedly changing beliefs about the insurgency, as well as interactions during the simulation, but nonetheless allows us to gauge the likely effects of an overall "hearts and minds" strategy, that is partially mixed with a costs-based attrition strategy.

We consider nine configurations of counterinsurgent and insurgent disciplines (summarized in Table 2). We will repeat each of these nine experiments when the population's commitment is distributed right-skewed (away from insurgency), normal, and left-skewed (towards the insurgency), resulting in 27 experiments.[14] Each experiment will be repeated 5 times and its results averaged. Because this is an initial modeling exercise, we set other parameters at reasonable values and do not test the effect of varying them.

[Table 2 Here]

Implications of the Model

Given that we varied two parameters at a time, we first consider the effect of varying the initial insurgent discipline while holding constant the counterinsurgent discipline. Thus, the first three results show insurgent disciplines at 0.25, 0.5, and 0.75 while the counterinsurgent discipline is set to 0.25 for all three. Then we repeat the exercise with counterinsurgent discipline at 0.5 and then 0.75. Table 3 highlights in bold the values that are changed in each experiment.

[14] We carried out each of these experiments using the Jammu and Kashmir region only as well as all of India. The results are quite similar and so we report only the results for all of India.

We report both the mean number of insurgents in each of these representative runs along with the corresponding plot that demonstrates the dynamics of the insurgency over time. Each row reports the results of experiments in which population commitment is right-skewed, normally distributed, and left-skewed. Sample plots for the case in which the population is normally distributed are in the Appendix and can be referenced by the appropriate plot letter.

Table 3 gives the results of varying insurgent disciplines, holding the counterinsurgent discipline constant. The results of these experiments (reading down the rows) show that as insurgents show increasing levels of discipline and self-control, they are able to win support for their cause. The results are fairly strong in the first three conditions (plots H,F,D), but nonlinear in conditions 4, 5, and 6 (plots G,A,C), but again consistently increasing when counterinsurgents are also highly disciplined (conditions 7,8,9; plots E,B,I). As the population increasingly leans towards the insurgency (across columns: right skew, normal, left skew), the number of insurgent collaborators also increases.

[Table 3 Here]

These initial results suggest that if insurgents can exhibit enough self-control to form cooperative relationships with civilians, and the counterinsurgents are not as involved in providing comparable social benefits, then the insurgency will grow. This is a similar result as famous practitioners of insurgency might expect (Tse-tung 1987). Where insurgents are helping civilians, they are also growing stronger. Where there is a contest for control, then the insurgency often struggles to compete (See Kalyvas 2006).

Turning to changes in counterinsurgent disciplines while holding the insurgent discipline constant, as counterinsurgents exhibit more discipline, they are also able to weaken

the insurgency. As they lose self-control, the insurgency is strengthened. In contrast to the previous results, which were strongest in conditions 1-6, these results appear fairly strong across all nine-experiments where population commitment is normally distributed. There appears to be some evidence of a nonlinear relationship in when examining the trend as one discipline value increases – this may be a result of the overall ratios between insurgent and counterinsurgent collaborators within the model. Like the previously reported results, as the population increasingly leans towards the insurgency, the insurgency strengthens.

[Table 4 Here]

The results of these experiments suggest the following hypotheses:

H1: When insurgents ***increase in discipline***, this leads to an ***increase in insurgent strength***

H2: When counterinsurgents ***increase in discipline*** towards the population, this leads to a ***decrease in insurgent strength***

H3: When counterinsurgents ***decrease in discipline,*** this leads to an ***increase in insurgent attacks***

H4: As the population's sentiment ***increasingly favors the insurgents***, this leads to an ***increase in insurgent strength***

Although most of the relationships appear to be linear, there appears to be some suggestion nonlinearities in the results where increasing benefits only increases the strength of the insurgency for middling values, or vice versa. In the empirical analysis that follows, we consider whether both linear and nonlinear relationships exist.

Empirical Analysis – Violence in India

To investigate the process of violence between insurgents and counterinsurgents, we restrict our initial investigations to a single country. This allows us to make the modeling more tractable as well as establish some baseline expectations. Including other states, the influence of external actors, cross-border interactions, and other transnational processes could add more realism to the model, but at this stage, these additions would also increase the complexity of modeling exercise by adding new actors, parameters, and modes of interaction. Instead, we focus on one country, India, and its experience with political violence. India is a unique laboratory for this inquiry as it has experienced diverse forms of violence since independence from Britain, it is the world's largest democracy, and one of the most frequent receivers of domestic and transnational terrorism.[15] India has been plagued by separatist inspired terrorism in Kashmir since 1989, deadly ethnic riots, a Maoist insurgency that has spread across several states, and a violent campaign in the 1980s in the Punjab region (Gupta 2007, Piazza 2010). We use this country to investigate insurgent-counterinsurgent dynamics with the expectation that India will provide multiple conflicts, types of violence, and a long history of these interactions.

[Figures 1 and 2 about here]

Research Design

To test hypotheses from the computational model, we collected events data within India from 1998 to 2010 (See Figures 1 and 2). We have data on thousands of events during this

[15] According to the Global Terrorism Database (http://www.start.umd.edu/gtd/), India experienced 4,799 incidents from 1970-2008.

period that relate to actions perpetrated by the state against the insurgents, actions by the insurgents against the state, actions by the state against the population, and actions by insurgents against the population.[16] These data are unique for several reasons. Typically, studies on civil war and insurgency are cross-national and focus on highly aggregated data (at the country-level, by year). By contrast, our data include all events that can be deciphered from news reports in India each day. We aggregate them by week and by month here, but they can be disaggregated or aggregated to most common temporal units depending on the question the researcher would like to address. In addition to the actual events, we also have coded data on sentiment towards each actor by each actor.[17] To generate these sentiment data, we identify texts created by individuals (such as blogs, news stories, diaspora sources), then use a coder which identifies the actor who is expressing the sentiment and the actor the sentiment is directed towards. The sentiment verbs were identified and rated on scale by a group of linguists. In sum, we create data that suggests on a given day that Actor A is angry/happy with Actor B. These data, in essence, are polling data from places and locations where it is difficult or near impossible to gather such data.[18] As mentioned above, these data are dyadic, but they are also coded each day for India from 1998 to 2010. These data can then be aggregated to the day, month, or year.

Data

One way to study multi-actor conflicts unfolding over time on a day to day basis is through the collection and analysis of disaggregated event data. Event data are "day-by-day coded

[16] EVENTS DATA FN1

[17] We thus have data on the Insurgent's sentiment towards the Counterinsurgents and Population, the Population's sentiment towards the Counterinsurgents and Insurgents, and the Counterinsurgent's sentiment towards the Population and Insurgents. The Counterinsurgent's sentiment is not a parameter in the computational model and is not used in the econometric model.

[18] A Defense Advanced Research Projects Agency seeding project funded SAE's efforts to develop automated sentiment software.

accounts of who did what to whom as reported in the open press," which "offer the most detailed record of interactions between and among actors" (Goldstein 1992, 369). Most basic event datasets code the (1) actor taking the action, (2) the target receiving the action, (3) the action itself (the event), and (4) the date of the action/event (usually the day each event takes place). Some example events coded in political violence datasets include armed attacks/conflict, nonviolent protests, negative statements, positive statements, low-level agreements between actors (e.g. ceasefires), and high-level agreements between actors (e.g. regional territorial autonomy).

Until recently, the collection of event data was cost prohibitive for most researchers. Historically, event data were coded manually, leading to problems such as low inter-coder reliability and a lack of coder attention to detail over time as they spend countless hours reading documents, identifying events from text, and classifying them into different categories.

In the early 1990s, the Kansas Events Data System (KEDS) demonstrated that the collection of events data could be automated (see Schrodt and Gerner 1994, Schrodt, Davis, and Weddle 1994). With automated coding, the coding rules are transparent, the data are easily and quickly reproducible, the data can be regenerated using alternative coding schemes, and the data are unaffected by individual coders' biases, as well as reducing the time required for coding from hundreds of hours of human labor to mere minutes once the input texts have been formatted and coding dictionaries prepared. KEDS and its open-source successor, the Text Analysis By Augmented Replacement Instructions (TABARI)

program[19], radically changed the information that is available to conflict scholars. The coded actions run the gamut from positive and negative statements to bombings to political compromises to armed raids. The result is a record of publicly recorded events, and the actors, targets, and locations associated with each event. Employing automated coding methods allows the collection of massive amounts of pertinent information on civil conflict while also eliminating inconsistencies, coder fatigue, and coding time associated with human coding. The result is a numeric representation of an event in the form of "someone does something to someone else" on a certain day.

Strategic Analysis Enterprises (SAE) Inc. is developing the next generation of automated natural language processing tools to code the conflictual and cooperative behavior of multiple state, sub-state, and nonstate actors. Previous coders commonly employed a "sparse-parsing" technique to extract the subject, verb, and object from a sentence and determine the appropriate codes using pattern matching on actor and verb dictionaries.[20] The SAE Text Analysis Suite (SAEtext) uses a part of speech tagger together with a chunk-style parser, and lemitizer to perform extractions. The key difference is that more grammatical information is available to guide all stages of the process. There are grammatical "sanity checks" (e.g., verbs must actually be verbs) as well as grammatical guidance in processes such as seeking the source and target of a verb. SAE provided the use of their coder to create the data for this analysis.

In any instance, machine coded data are only as good as the dictionaries used to code them. Given our theories about micro-level processes and our belief about the number of

[19] See http://raven.cc.ukans.edu/~keds/index.html for information on the KEDS and TABARI projects. Also see Schrodt (1996; 2006) for the respective codebooks.
[20] TABARI recognizes pronouns and dereferences them. It also recognizes conjunctions and converts passive voice to active voice (Schrodt 1998).

actors involved in civil conflicts, we attempt to make the actor dictionaries as extensive and disaggregated as possible. Human coders collect terms on any major players in society including generic terms (businessmen, religious leaders, dissidents, protestors, or anyone else without a specific name). We also made use of the SAEtext actor finder program, which identifies potential actors in texts that do not appear in dictionaries. We perused these lists by ranking the number of hits each actor received in our corpus and added the ones to our dictionaries that seemed most important.

In this experiment, we analyzed a dataset compiled for India. The dataset was compiled using the SAEtext program from a Lexis Nexis corpus containing multiple news sources (BBC, AFP, the Statesman, etc.). The actor dictionary for this case was borrowed from Project Civil Strife (PCS) and is extensive.[21] For example, it includes actors from Prime Minister Monmohan Singh and the Indian National Congress all the way down to Tiger Memon, a Mumbai Gangster. In addition to thousands of unique individuals specified, the Indian actor dictionary captures individual political, social, religious and dissident groups and leaders. All told, the actor dictionary for India includes 4,899 terms.

The events are coded according to a verb dictionary. Our verb dictionary is a modified CAMEO verb dictionary. Verbs and verb phrases are assigned a category based on the CAMEO coding scheme. The verb dictionary is ever changing as new phrases are added and old, no longer needed phrases are removed. The dictionary used on this project is a

[21] See Shellman (2008) for more information.

product of a collaborative effort of KEDS phrases, SAE phrases, and Project Civil Strife Phrases.[22]

While the original data code individual actions, these events are often scaled on a hostility-cooperation continuum. Such scaled data are often used in studies of international (e.g. Goldstein and Freeman 1991) and intranational (e.g., Shellman et al. 2010) political interactions. The scaled data were generated using the CAMEO scale.[23]

Although the data set is capable of functioning on a highly disaggregated level, our experiment called for a degree of aggregation. Our agent based model was parsimonious and employed only three classes of actors: insurgents, counterinsurgents, and civilians. In order to test the findings of the ABM, we mapped our actors into these three categories. All government actors, from the executive office to ministry of finance to military and police, were operationalized as counterinsurgents. Social actors including but not limited to teachers, students, refugees, workers, and businesses were placed in the civilian group. Lastly, rebels, insurgents, terrorists, and dissidents were placed in the insurgent group.

Directed-dyadic actions between these groups are then measured on a monthly basis. Measures include counts of events, Goldstein weighted totals (i.e., sum of dyadic scaled events), and Goldstein weighted averages (i.e., average of scaled events) of all positive, negative, cooperative, violent, and hostile actions. As outlined above, we also have sentiment data that is created from texts that refer to actors feelings towards other actors positively/negatively or in a hostile/cooperative manner.

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[22] Research Assistants from the University of Kansas, University of Georgia, Penn State, William & Mary, Lockheed Martin and SAE have all added and subtracted phrases as the verb dictionary has been used in multiple projects of late.
[23] See http://web.ku.edu/~keds/cameo.dir/CAMEO.SCALE.txt.

Measures:

The final dependent variable for the study is a measure of insurgent violence.[24] While this is not a perfect predictor of insurgent strength or numbers, it is highly related. In Afghanistan, for example, attacks against US forces are at their highest level since the US-led invasion in 2001. Most observers, military and otherwise, assume that Taliban troop levels are also increasing. According to a US intelligence estimate in 2009, the Taliban increased their numbers fourfold from 2005-2009.[25] This corresponds with dramatic increases in casualties for US forces.[26] We use the events data to collect all violent acts by insurgents against the population and state. As robustness checks, we also use separate measures of all activity by insurgents against the population and state.

[Figure 3 about here]

Based on the predictions from the computational model, the key independent variables need to measure costs and benefits by both insurgents and counterinsurgents applied to members of the population (See Figure 1). These actions within actor dyads do not exist in standard conflict data. We employ measures from the data described above. First, we aggregate all negative interactions by insurgents against the population (Insurgent Hostility (Population)) and all positive actions by insurgents against the population (Insurgent Cooperation (Population)). Second, we aggregate all negative interactions by the state against the population (State Hostility (Population)) and all positive actions by insurgents against the population (State Cooperation (Population)). These four variables are

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24 In a robustness check, we use a measure of all insurgent activity and find similar results.
25 "Taliban Growth Weighs on Obama Strategy Review," Reuters, 9 October 2009. Found online at: http://www.reuters.com/assets/print?aid=USN09496447
26 For a graph of this increase over the course of the war, see http://www.icasualties.org/oef/ByYear.aspx

indicators for these actions within the computational model, depicted next to the arrows in Figure 1, and allow us to test hypotheses 1 and 2. We also want to investigate how sentiment towards both Insurgents and the State influences number of insurgents over time (the bottom portion of Figure 3). While a simultaneous two-stage approach may be an appropriate way to estimate this model, we cannot do so for several reasons. Most importantly, the number of insurgents is a count variable. Standard two-stage least-squares approaches require a continuous variable.[27] Also, the dynamic nature of the data would force us to make some "incredible" assumptions about the other variables in the equation, i.e. that they are all exogenous (Kennedy 2006, 192). While we know estimating each equation independently may introduce bias in the coefficients, especially in the second stage, we do not feel the alternatives can reduce or eliminate this bias.

[Tables 5, 6, and 7 about here]

Results/Discussion

Table 5 displays the results from our initial statistical models. We present four models varying the dependent variable and unit of temporal observation.[28] In the first model, we use a dependent variable of the Population Sentiment towards the State using a weekly temporal unit of aggregation. In the second model, we use a weekly measure of the Population Sentiment towards Insurgents as the dependent variable. In the third and fourth

[27] As a robustness check, we did estimate a series of modified two-stage least squares (2SLS) models. In brief, we predicted sentiment for each side in the first stage using cost/benefit variables for the actor dyads, then used these predictions in the second stage as instrumental variables for sentiment. Since insurgent attacks is not a continuous variable, these data violate a critical assumption of 2SLS regression models. The results for this approach are similar except the instrument for population sentiment towards insurgent is not significant. The instrument for population sentiment for the state has a larger coefficient estimate and smaller standard errors and is consistent with the notion that as people feel more positive towards the State, insurgent attacks are likely to decline.

[28] We do this as want to make sure our inferences are robust to the temporal unit of aggregation used (Shellman 2004).

models, we use the monthly unit of aggregation and use the same dependent variables as the first two models. For independent variables, we use measures of hostile and cooperative actions by the state and insurgents.

The results for hostile cooperative actions on sentiment are fairly stable across the four models. Insurgent hostile actions against the population seem to decrease sentiment or support for the state. Hostile actions by the insurgents against the population does not, however, seem to influence support for the insurgents. State cooperative actions towards the population also tend to decrease support for the insurgency as expected. By contrast, state cooperative actions towards the population also are associated with decreases in support for the state. These results are consistent yet contrary to expectation. We expected these actions to increase support for the state. Table 5 examines the intermediate influence of hostile cooperative acts on sentiment. We are most interested in how this ultimately explains a rise or fall in the number of insurgents/insurgent violence. Table 6 displays the results for models using insurgent violence as the dependent variable. In this table we examine models that vary the temporal unit of observation and vary the use of a lagged dependent variable.[29] Recall, that H1 asserts that increasing discipline (which in practice is increasing benefits or cooperative actions) by insurgents should increase insurgent strength/violence. Costs and benefits should influence sentiment, which will in turn influence insurgent attacks. Population sentiment toward the state operates as expected, but misses conventional levels of significance in three of the four models. As sentiment towards the state increases, insurgent attacks may decline. Again, these results are not consistent and thus give mixed support to H2 and H3. Population sentiment towards insurgents also has a

[29] We also estimated models using multiple lags. In general, additional lags improve model (as high as seven lags), but do not change the relationship between the dependent variables and independent variables of interest.

negative coefficient in all of the models in Table 6. In two for the four, the result can be distinguished from zero, but it is not in the expected direction. Thus, the results do not support H4. We also control for hostile and cooperative acts from the State to the Insurgents as this will likely influence insurgent violence. All of these measures seem to increase insurgent attacks. We also use a squared term as the hostile/cooperative actions could have a curvilinear effect on violence (Shellman 2009). Our results support this claim. Finally, we control for lagged violence and find it is positively related to attacks. In another set of models in the appendix (Models A2 and A3), we re-estimate the monthly data using Bayesian methods.

Conclusions and Future Directions

This paper couples agent-based modeling with events data analysis to understand the localized dynamics of insurgency. The research is attempting to meld computational models of insurgency with automated events and sentiment data within India from 1998 to 2010. We contended that, despite significant attention devoted to insurgency and counterinsurgency, little attention has been given to the important role of the population. We then developed a model in which insurgents and counterinsurgents interacted with a population both heterogeneous in its commitment to the insurgency and its willingness to change its level of support. Initial results suggest that violent strategies undermine the parties that use them, whereas approaches that emphasize winning the hearts and minds through the provision of various benefits may be most constructive for insurgents and counterinsurgents alike.

Using the data from India, the results of our investigation are mixed. We find that population sentiment towards the state decreases insurgent attacks. Contrary to expectations, population sentiment towards insurgents is also negatively related to insurgent attacks. As we work towards tightening the consistency between the empirical and computational model, we need to investigate why this outcome is occurring. Results using Bayesian models (see appendix) provide similar results. Since the computational model is Bayesian, using Bayesian estimation likely provides a tighter link between theory and estimation. We plan to estimate Bayesian hierarchical models at different temporal aggregations to attempt to get a tighter link between the computational models and statistical models.

Since we only consider India, the empirical tests need to be extended to other countries, which will be one of our next steps. We are collecting data on a number of other Southeast Asian countries and intend to test the model cross-nationally. Hopefully, extending the analyses to other countries and ultimately other regions can help generalize the results of the simulations and empirical tests.

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Table 1: Summary of Model Parameters and Default Values

	Agent Attributes			
Parameter Name	**Description**	**Type**	**Default Value**	**Notation**
Move Distance	The distance that agents are able to move, in cartographic degrees.	Float	Calculated dynamically	γ_i
Interaction Radius	Radius of the agent's sphere of influence. Agents interact with the closest agent to them within this radius. Radius is defined in cartographic degrees (A degree in India is equal to 103 km on average).	Float	Calculated dynamically	υ_i
Counterinsurgent and Insurgent Vision	The size of a Von Neumann neighborhood within which agents can inspect zones of control adjacent to them to determine the presence of insurgents or counterinsurgents.	Int	3, for both insurgents and counterin-surgents	$\phi^{\kappa,\lambda}$
Percentage of Insurgents	An integer value representing the percentage of the population that is desired to be insurgents. (note: since agents are created using a statistical distribution this percentage will be true on average, but the actual number of insurgents will vary for individual simulations)	Int	10	α^{λ}
Counterinsurgent and Insurgent Resources	Determines the constant resource endowment for each individual faction. Higher resources correlate to higher probabilities of initiating economic interactions.	Float	0.5	$\rho^{\kappa,\lambda}$
Belief Radius	The radius of the area within which agents' commitment are used to calculate beliefs. Defined in cartographic degrees.	Float	Calculated dynamically	μ_i
Commitment	Defines an individual's level of overall commitment to the insurgency, in a range from 0.0 to 1.0	Float	$N(\pi = 0.5, \sigma = 0.16)$	χ_i

Belief	An agent's belief about the local strength of the insurgency, according to the types of agents within that agent's belief radius. (see "belief updating")	Float	0.5	β_i
Discipline	Represents an agent's self-discipline and restraint, which influences its decision to give benefits or impose costs.	Float	For civilians: U(0,1) For all others: 0.5	δ_i
Counterinsurgent and Insurgent Capacity	Represents a faction's ability to employ selective violence. This is the probability, between 0.0 and 1.0, that a political agent will assassinate a denounced enemy collaborator if given the opportunity.	Float	0.7	$\sigma^{\kappa,\lambda}$
Responsiveness	The actual responsiveness of an individual agent, which determines the amount by which an agent's commitment may change during an interaction. The maximum value is determined by the *Responsiveness Range* parameter *R*.	Float	U(0, R)	ω_i
Counterinsurgent and Insurgent Collaboration Bound	The upper (lower) bound of counterinsurgents' (insurgents') commitment spectrum. Calculated based on desired percentage of counterinsurgents and insurgents, as well as the skewness of the population distribution.	Float	Calculated dynamically	$\psi^{\kappa,\lambda}$
Counterinsurgent & Insurgent Commitment Bound	The upper (lower) bound of counterinsurgents' (insurgents') commitment spectrum. Calculated based on desired percentage of counterinsurgents and insurgents, as well as the skewness of the population distribution.	Float	Calculated dynamically	$\theta^{\kappa,\lambda}$
	Model Parameters			
Parameter Name	**Description**	**Type**	**Default Value**	**Notation**
Administrative Boundaries	A drop down menu that allows the user to choose the location of the simulation from among 25 SE Asian countries.	NA	India	-

Province	The specific province within the country that the simulation will be limited to.	NA	Entire country	-
Population	Total number of agents (civilians + insurgents + counterinsurgents) to be generated in the simulation.	Int	1000	N
Skewness	Influences the shape of the generated commitment distribution, making it tend towards one side or the other. Typically ranges from between -2 and 2.	Float	0	S
Denunciation Threshold (Denounce Risk)	Defines the threshold that the utility of denunciation must exceed before an agent will denounce an enemy collaborator.	Float	0.4	T
Counterinsurgent and Insurgent Social Advantage	Represents the popularity or strength of the ideological message shared by a given faction. Increases or decreases the probability that a faction's social appeals will be effective by a fixed percentage.	Float	0	$A^{\kappa,\lambda}$
Responsiveness Range	Defines the maximum responsiveness which any individual agent can have. The individual responsiveness attribute ω is drawn from U(0,R).	Float	0.5	R
Insurgent Concealment	Counterinsurgents can only perceive insurgents if their "presence" within a single zone of control exceeds this threshold.	Float	0.25	H

Insurgent Audacity (or level of guerilla strategy)	Insurgents will flee from their current zone to an adjacent zone if the local counterinsurgent presence exceeds this threshold.	Float	0.5	D
Civilian Memory	Civilians will remember this number of interactions with each faction, and determine that faction's popularity by the number of positive interactions divided by total interactions within that set.	Int	75	E
Move Distance Factor	The size of the geography is divided by this value to obtain the move distance for each agent.	Float	300	M
Interaction Radius Factor	The size of the geography is divided by this value to obtain the maximum interaction radius for each agent.	Float	50	F

Experiment	Counterinsurgent Discipline	Insurgent Discipline
A	0.5	0.5
B	0.75	0.5
C	0.5	0.75
D	0.25	0.75
E	0.75	0.25
F	0.25	0.5
G	0.5	0.25
H	0.25	0.25
I	0.75	0.75

Table 2: Summary of Initial Experiments; Note: Parameters that do not vary in initial runs: 1000 iterations, responsiveness higher bound =0.5, the total population is 1000 agents with 5% insurgents and 10% counterinsurgents, social advantage for both groups is 0, resources for both groups is 0.5, overall denunciation risk is 0.4, and assassination capacity for both groups is 0.7.

The Effect When Insurgents Exercise Self-Control							
Condition	**Insurgent Discipline**	Counter Insurgent Discipline	# I Collab. (Left Skew)	# I Collab. (Normal)	# I Collab. (Right Skew)	I Discipline Trend	Pop. Skew Trend
1 (Plot H)	0.25	**0.25**	223.65	437.63	439.6	Insurgency Strengthens (down rows)	No significant change (across columns)
2 (Plot F)	***0.5***	0.25	459.98	480.35	471.42		
3 (Plot D)	***0.75***	0.25	548.59	564.03	576.62		
4 (Plot G)	0.25	***0.5***	55.18	104.95	121.25	Insurgency Strengthens / Nonlinear (down rows)	Insurgency Strengthens (across columns)
5 (Plot A)	***0.5***	*0.5*	146.9	128.05	179.9		
6 (Plot C)	***0.75***	*0.5*	242.08	229.55	354.43		
7 (Plot E)	0.25	***0.75***	44.07	37.01	50.56	Insurgency Strengthens (down rows)	Insurgency Strengthens (across columns)
8 (Plot B)	***0.5***	*0.75*	65.74	72.92	80.16		
9 (Plot I)	***0.75***	*0.75*	104.876	107.79	277.89		

Table 3: Results of models in which *insurgents* are increasingly disciplined; Note: Parameters that do not vary in initial runs: 1000 iterations, responsiveness higher bound =0.5, the total population is 1000 agents with 5% insurgents and 10% counterinsurgents, social advantage for both groups is 0, resources for both groups is 0.5, overall denunciation risk is 0.4, and assassination capacity for both groups is 0.7.

The Effect When Counterinsurgents Exercise Self-Control							
Condition	**Counter Insurgent Discipline**	Insurgent Discipline	# I Collab. (Left Skew)	# I Collab. (Normal)	# I Collab. (Right Skew)	I Prob Trend	Pop. Sentiment Trend
1 (Plot H)	0.25	**0.25**	223.65	437.63	439.6	Insurgency Weakens / Nonlinear (down rows)	Insurgency Strengthens (across columns)
2 (Plot G)	***0.5***	0.25	55.18	104.95	121.25		
3 (Plot E)	***0.75***	0.25	44.07	37.01	50.56		
4 (Plot F)	0.25	***0.5***	459.98	480.35	471.42	Insurgency Weakens / Nonlinear (down rows)	Insurgency Strengthens (across columns)
5 (Plot A)	***0.5***	*0.5*	146.9	128.05	179.9		
6 (Plot B)	***0.75***	*0.5*	65.74	72.92	80.16		
7 (Plot D)	0.25	***0.75***	548.59	564.03	576.62	Insurgency Weakens (down rows)	Insurgency Strengthens (across columns)
8 (Plot C)	***0.5***	*0.75*	242.08	229.55	354.43		
9 (Plot I)	***0.75***	*0.75*	104.876	107.79	277.89		

Table 4: Results of models in which *counterinsurgents* are increasingly disciplined; Note: Parameters that do not vary in initial runs: 1000 iterations, responsiveness higher bound =0.5, the total population is 1000 agents with 5% insurgents and 10% counterinsurgents, social advantage for both groups is 0, resources for both groups is 0.5, overall denunciation risk is 0.4, and assassination capacity for both groups is 0.7.

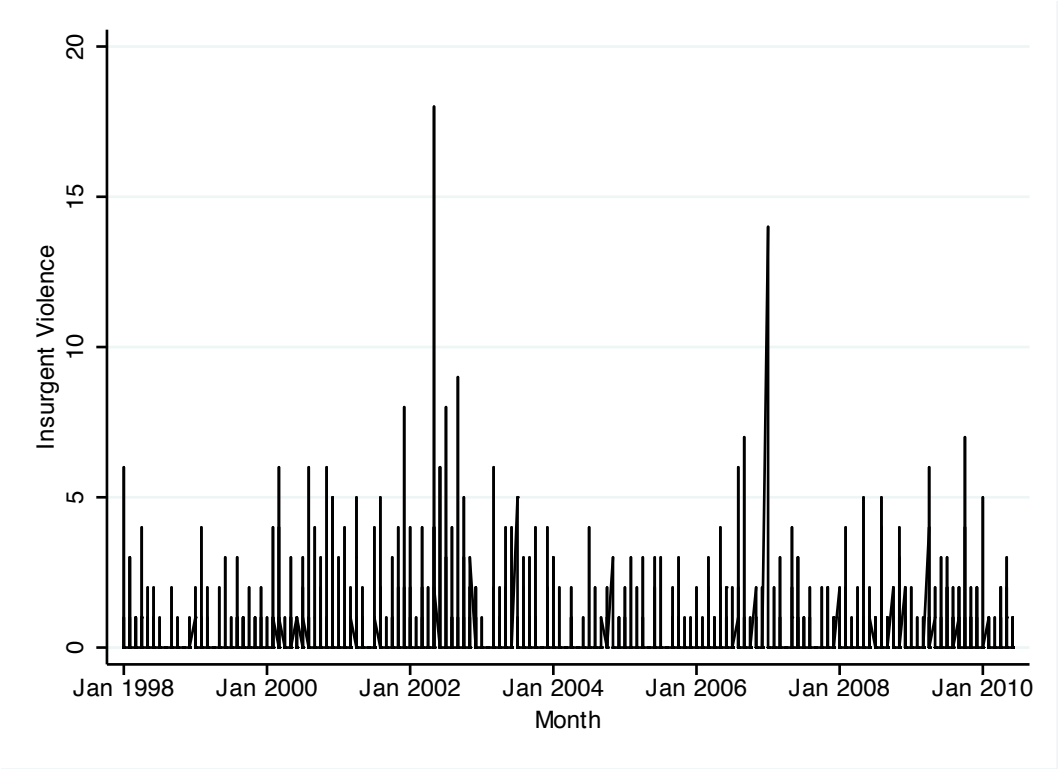


Figure 1--Monthly Total of Violent Insurgent Events in India, 1998-2010

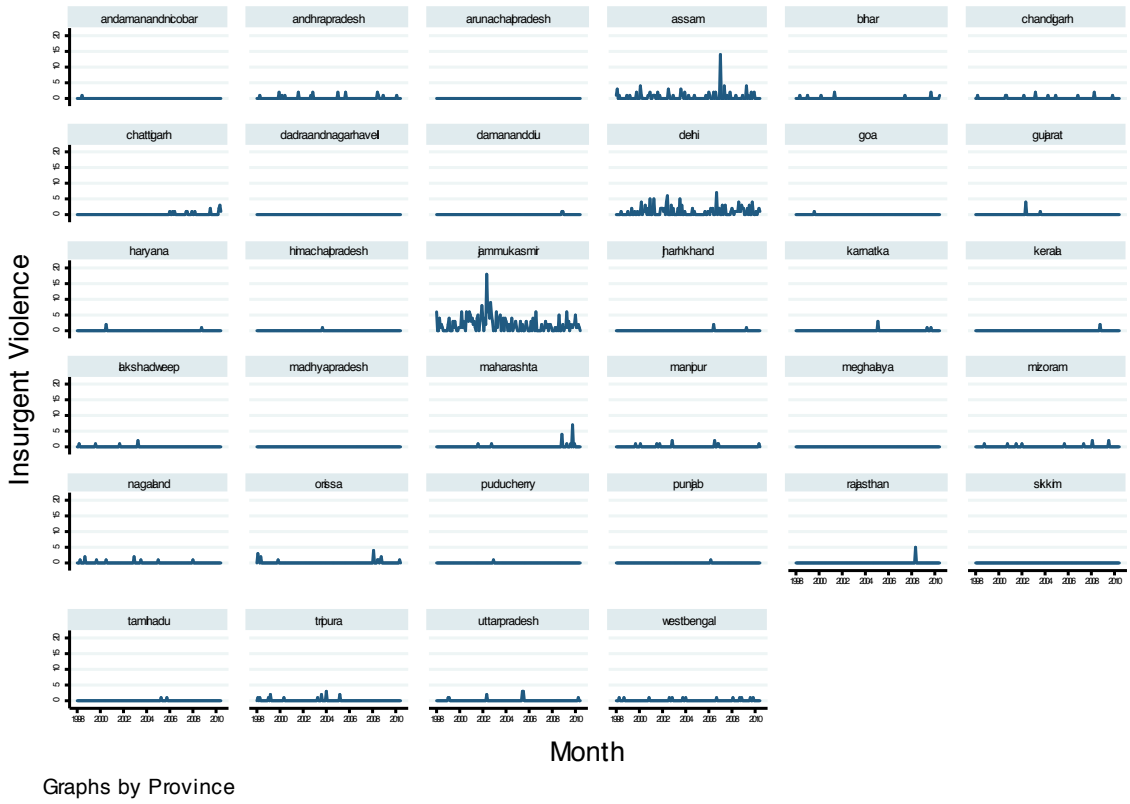


Figure 2--Monthly Insurgent Violence in India, by Province, 1998 to 2010.

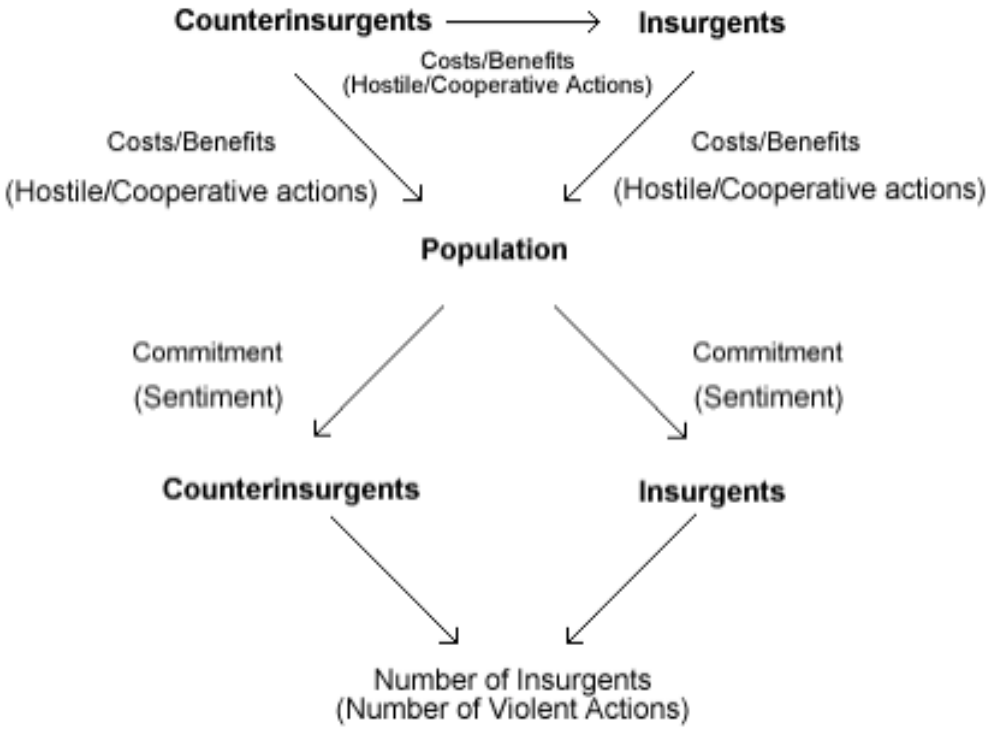


Figure 3--Graphical Representation of Computational Modeling Parameters and Associated Data to Measure these Parameters. *The items in bold are actors in the computational model and aggregate actors in the events data. The items by the arrows are the actions available to these actors in the computational model. Below these actions, are the events and sentiment data used to measure these actions.*

Table 5--Insurgent/State Hostility/Cooperative Actions Towards the Population, India 1998-2010.

Variable	Population Sentiment to State (Weekly)	Population Sentiment to Insurgents (Weekly)	Population Sentiment to State (Monthly)	Population Sentiment to Insurgents (Monthly)
State Hostility (Population)	-0.036	-0.022	-0.018	-0.004
	(0.032)	(0.015)	(0.020)	(0.003)
State Cooperation (Population)	-0.059**	-0.006**	-0.098***	-0.018**
	(0.024)	(0.002)	(0.027)	(0.007)
Insurgent Hostility (Population)	-0.099***	-0.020	-0.407***	-0.043
	(0.027)	(0.015)	(0.110)	(0.042)
Insurgent Cooperation (Population)	-0.099	0.012**	-0.168	0.031
	(0.119)	(0.005)	(0.214)	(0.060)
Constant	-0.015***	-0.002*	-0.035***	-0.007
	(0.004)	(0.001)	(0.010)	(0.005)
	N=22,032	N=22,032	N=5,066	N=5,066
	R2=0.005	R2=0.003	R2=0.04	R2=0.01

Coefficient estimates are above the robust standard errors (clustered on province) in parentheses * p<0.10, ** p<0.05, ***p<0.01

Table 6--Effect of Events/Sentiment Data Variables on Insurgent Violence, India 1998-2010.

Variable	All Insurgent Violence (Weekly)	All Insurgent Violence (Weekly)	All Insurgent Violence (Monthly)	All Insurgent Violence (Monthly)
Population Sentiment (State)	-0.175 (0.116)	-0.192 (0.120)	-0.125* (0.064)	-0.092 (0.057)
Population Sentiment (Insurgents)	-0.428*** (0.111)	-0.301* (0.177)	-0.432 (0.351)	-0.203 (0.236)
State Hostility (Insurgents)	1.396*** (0.218)	1.153*** (0.169)	1.190*** (0.121)	1.073*** (0.140)
State Hostility Squared (Insurgents)	-0.089*** (0.015)	-0.082*** (0.013)	-0.093*** (0.011)	-0.104*** (0.018)
State Cooperation (Insurgents)	1.380*** (0.202)	1.242*** (0.200)	0.741*** (0.098)	0.606*** (0.094)
State Cooperation Squared (Insurgents)	-0.094*** (0.016)	-0.083*** (0.015)	-0.036*** (0.005)	0.031* (0.005)
Lagged Violence	--	1.252*** (0.218)	--	0.464*** (0.119)
Constant	-3.791*** (0.373)	-3.886*** (0.358)	-2.764*** (0.266)	-2.807*** (0.267)
	N=22,032 AIC=5123 BIC=5187	N=22,032 AIC=5049 BIC=5121	N=5,066 AIC=3141 BIC=3193	N=5,066 AIC=3117 BIC=3176

Coefficient estimates are above the robust standard errors (clustered on province) in parentheses * p<0.10, ** p<0.05, ***p<0.01

Table 7--Substantive Effects for Variables from Econometric Model

Variable	% Increased in Expected Counts	95% Confidence Interval	
Population Sentiment (Insurgents)	-35%	-48%	-19%
State Hostility (Insurgents)	304%	164%	519%
State Hostility Squared (Insurgents)	-8.5%	-11%	-6%
State Cooperation (Insurgents)	298%	167%	491%
State Cooperation Squared (Insurgents)	-9%	12%	6%
Lagged Violence	250%	128%	436%

The percentage change in expected counts is calculated from incident rate ratios.

Appendix

Model Extensions

The GIS framework allows us to consider additional geospatial factors that might be important in the model. The ethnic identity of an agent, for example, can be based on the ethnic composition of the geographical location. When the ethnicity parameter is activated (=1), then agents in the simulation receive an ethnic identity based on where they are located. This ethnic identity conditions the behavior of every type of agent, such that members of the same ethnicity are more likely to offer benefits to co-ethnics and costs to others, regardless of whether the interaction occurs between insurgents, counterinsurgents, and the population (or any combination).

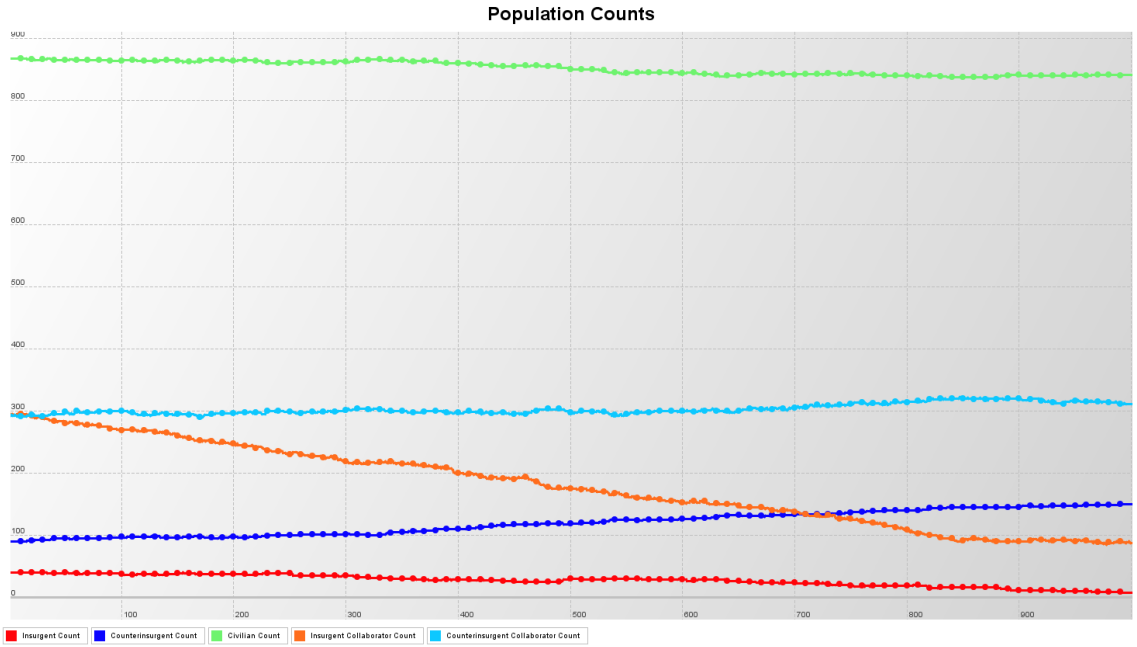
If the user selects the multiple interactions box this will set the parameter to true, and an insurgent will interact with every civilian within its neighbor radius. Otherwise, if the box is not checked, an insurgent will only interact with the closest civilian within its neighbor radius.

Table A1: Summary of Some Model Extensions

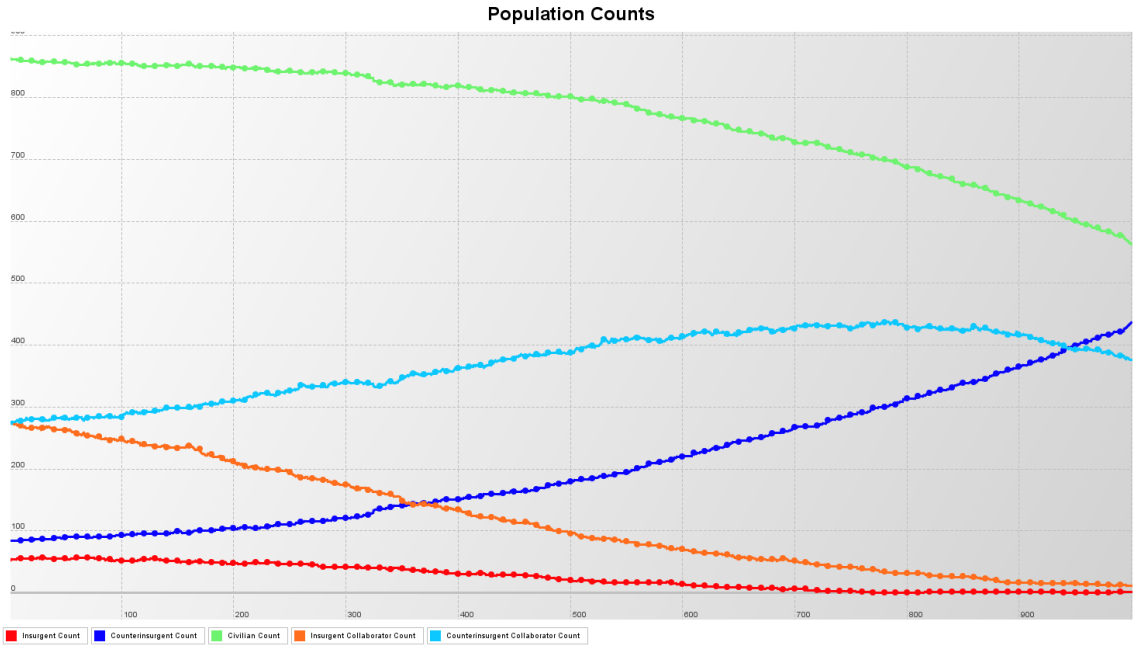
Benefits to same ethnicity	If set to true then when an agent encounters another agent of the same ethnicity, benefits will always be given. (not currently implemented)	Boolean	FALSE	
Costs to different ethnicity	If set to true then when an agent encounters another agent of a different ethnicity, costs will always be charged. (not currently implemented)	Boolean	FALSE	
Conversion to	A boolean value that, if set to true, allows	Boolean	False	

Counterinsurgents	civilians to convert to counterinsurgents if their commitment falls below the counterinsurgent commitment bound. If false then when a civilians commitment falls below the counterinsurgent commitment bound the civilian's commitment will be randomly redrawn in the civilian commitment range.			

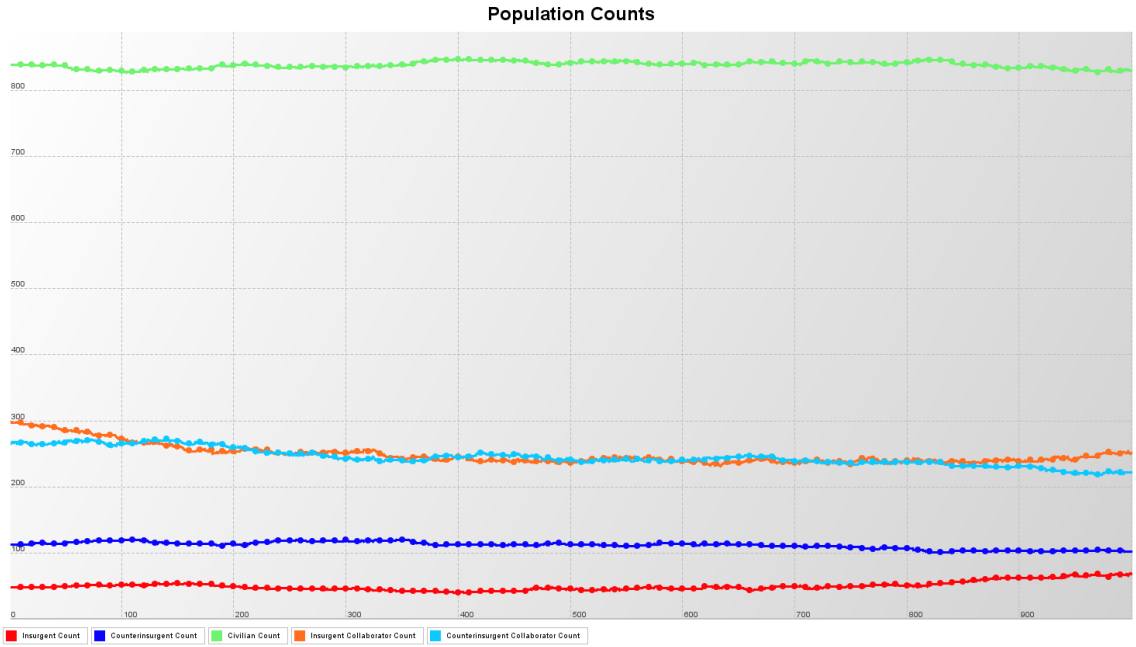
Experiment A



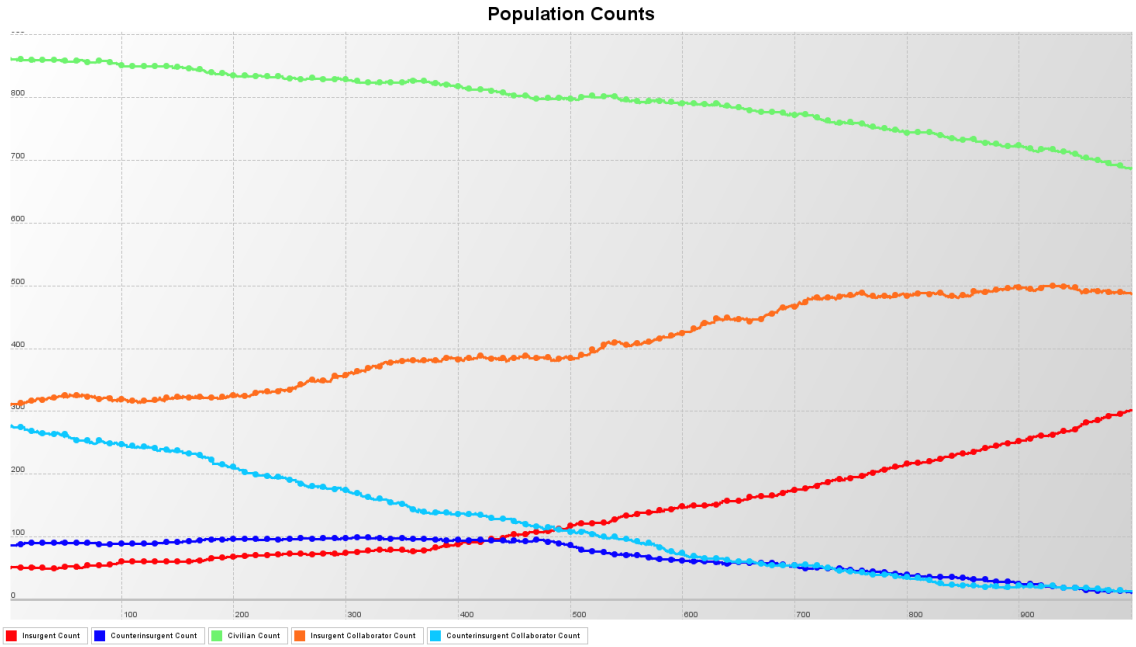
Experiment B



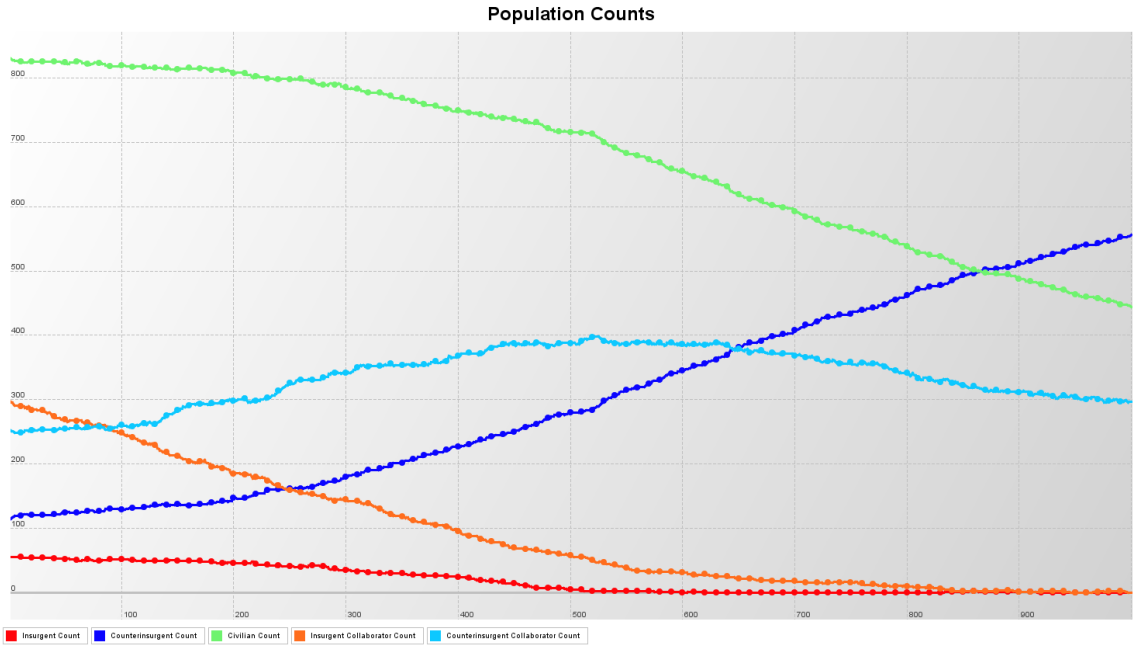
Experiment C



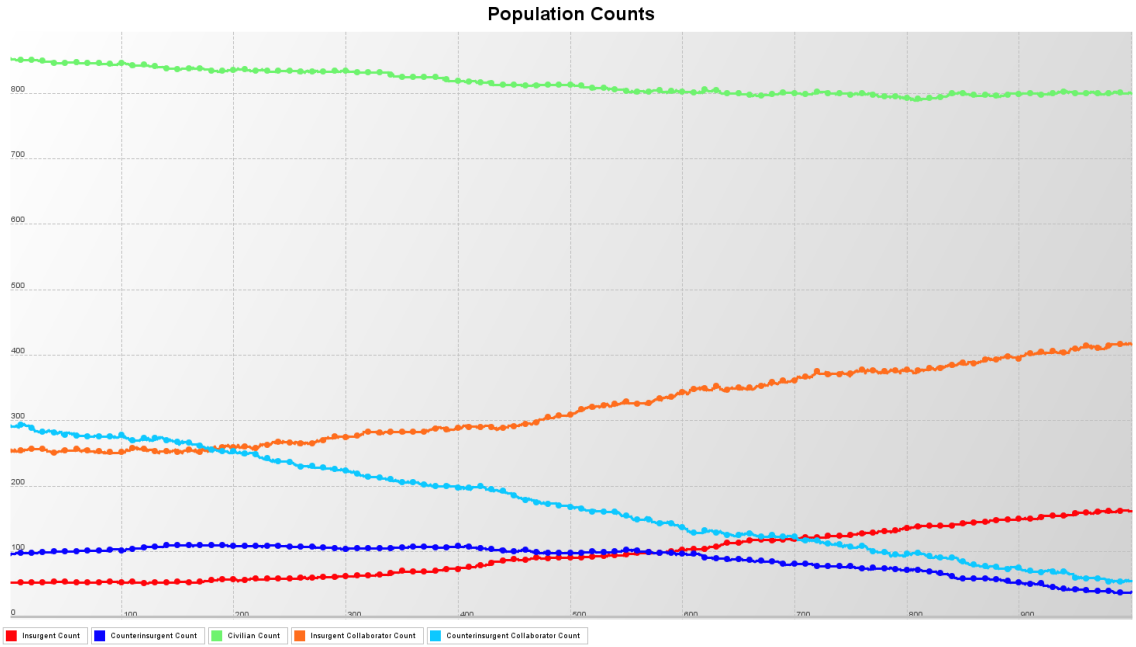
Experiment D



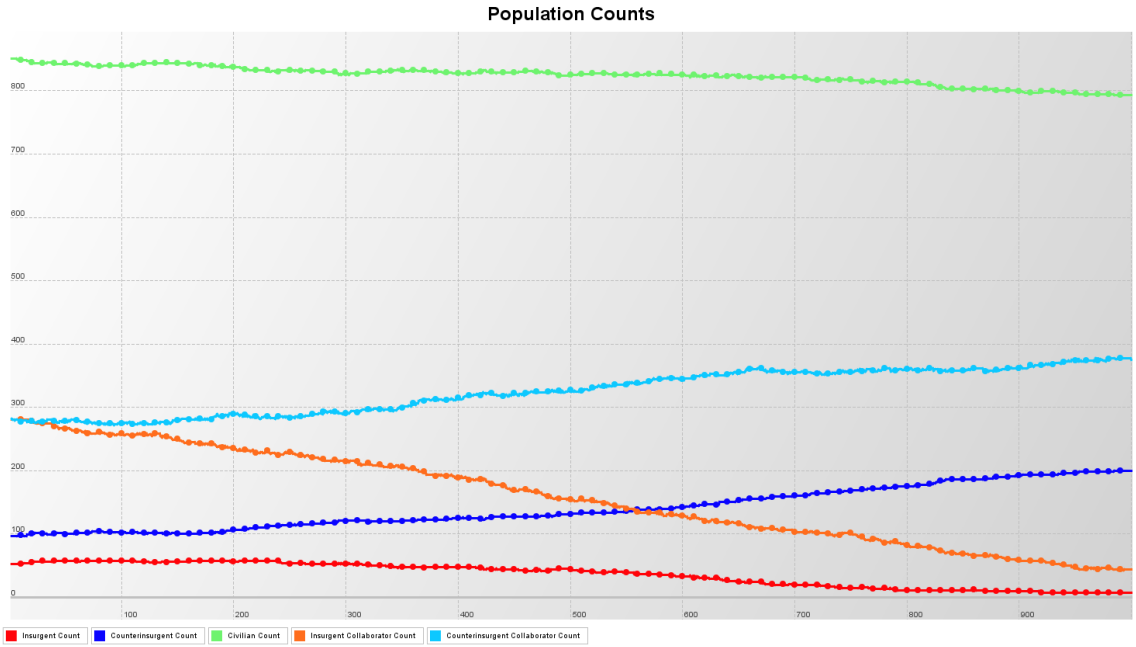
Experiment E



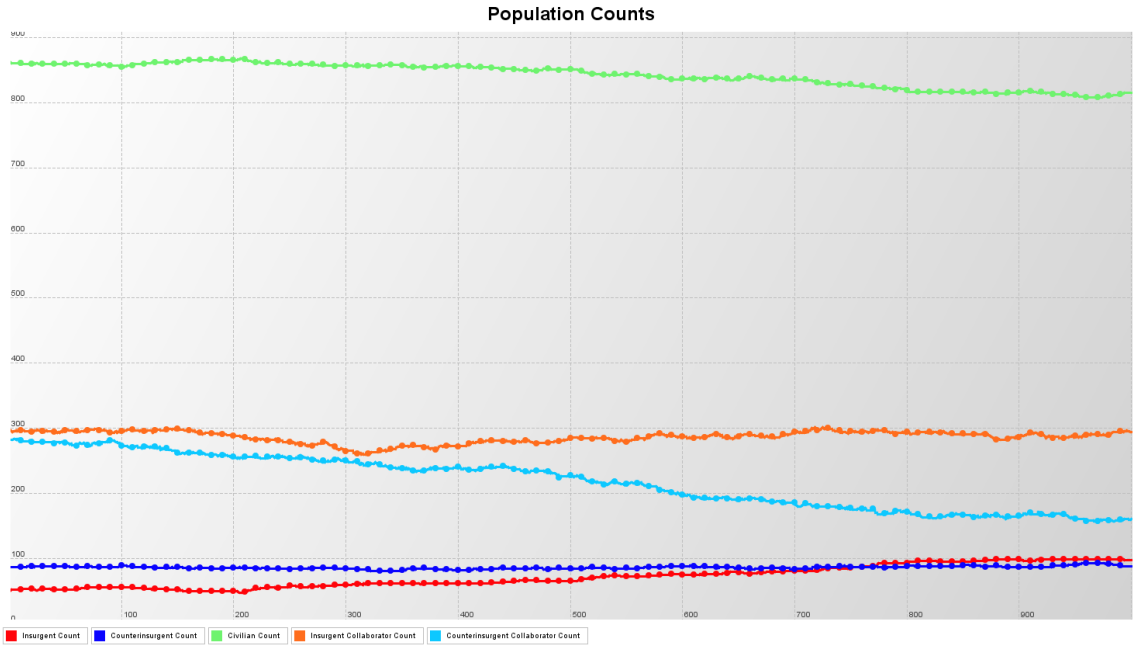
Experiment F



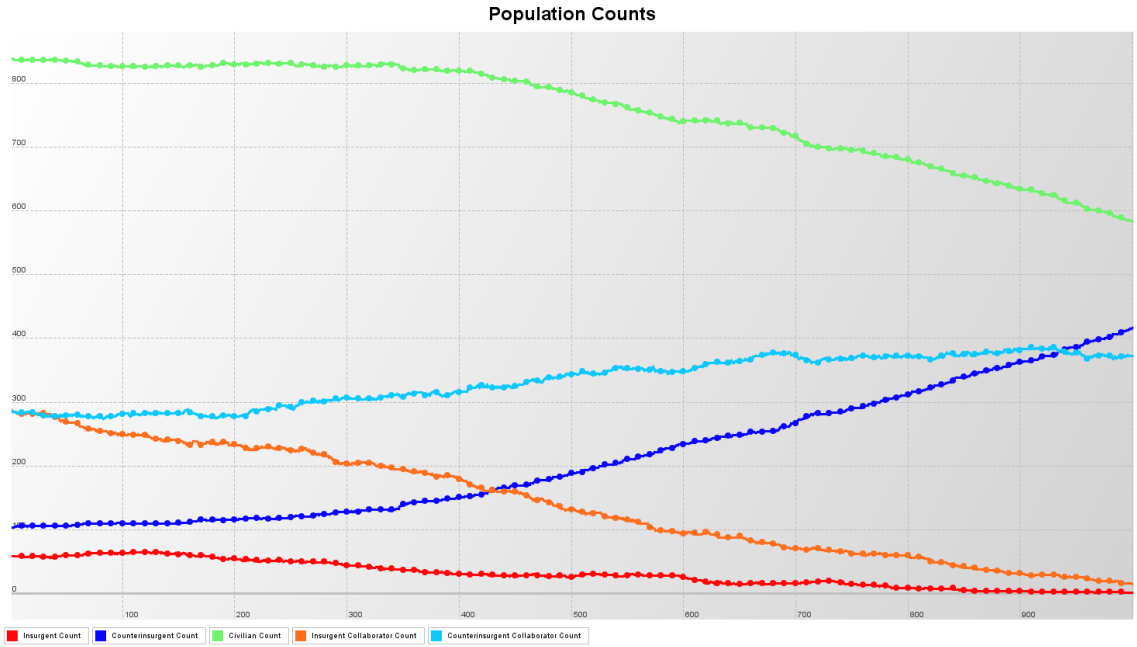
Experiment G



Experiment H



Experiment I



The parameters of the Bayesian models are estimated with Markov Chain Monte Carlo methods using R and JAGS. The model is similar to Gelman (2007, 345-353). All priors and hyper priors are normal distributions, except τ^{α} with a gamma prior distribution.

Table A2--Insurgent/State Hostility/Cooperative Actions Towards the Population, India 1998-2010. Bayesian Models.

Variable	Population Sentiment to State (Monthly)	10% to 90%	Population Sentiment to Insurgents (Monthly)	10% to 90%
State Hostility (Population)	-0.0182 (0.0158)	-0.0383 to 0.00238	-0.004 (0.005)	-0.011 to 0.003
State Cooperation (Population)	-0.0974 (0.0119)	-0.1125 to -0.0823	-0.018 (0.004)	-0.0234 to -0.0133
Insurgent Hostility (Population)	-0.406 (0.0423)	-0.461 to -0.353	-0.0431 (0.0140)	-0.0606 to -0.0252
Insurgent Cooperation (Population)	-0.171 (0.103)	-0.3012 to -0.0405	0.031 (0.034)	-0.0127 to 0.0749
Constant	-0.0353 (0.0129)	-0.0517 to -0.0185	-0.007 (0.004)	-0.013 to -0.002
	N=5,066		N=5,066	

Point estimates are above the standard errors in parentheses.

Table A3--Effect of Events/Sentiment Data Variables on Insurgent Violence, India 1998-2010. Bayesian Models

Variable	All Insurgent Violence (Monthly)	10% to 90%	All Insurgent Violence (Monthly)	10% to 90%
Population Sentiment (State)	-0.119 (0.049)	-0.182 to -0.0604	-0.092 (0.057)	-0.184 to -0.0466
Population Sentiment (Insurgents)	-0.489 (0.232)	-0.798 to -0.196	-0.203 (0.236)	-0.755 to -0.202
State Hostility (Insurgents)	0.917 (0.092)	0.800 to 1.033	1.073 (0.140)	0.761 to 1.030
State Hostility Squared (Insurgents)	-0.037 (0.005)	-0.0428 to -0.0306	-0.104 (0.018)	-0.0424 to -0.0279
State Cooperation (Insurgents)	0.726 (0.110)	0.588 to 0.869	0.606 (0.094)	0.582 to 0.910
State Cooperation Squared (Insurgents)	-0.029 (0.010)	-0.0414 to -0.0173	0.031 (0.005)	-0.0448 to -0.0175
Lagged Violence	--	--	0.464 (0.119)	-1.302 to 1.326
Constant	-2.729 (0.070)	-2.818 to -2.641	-2.722 (0.072)	-2.820 to -2.634
	N=5,066		N=5,066	

Point estimates are above the standard errors in parentheses