Modeling Civil Violence in Afghanistan: Ethnic Geography, Control, and Collaboration

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We develop a computational model to explore how ethnic geography shapes the distribution of violence in civil war. We seed the model with disaggregated data on ethnic settlement patterns in Afghanistan and calibrate the model parameters to fit empirically observed locations of violence against civilians. Our simulation suggests that (i) political actors are more likely to attack civilians in heterogeneous areas where members of one ethnic group are exposed to members of a rival group; (ii) violence directed at civilians occurs with greater frequency in locations where one political actor exercises hegemonic but incomplete territorial control (relative to areas of complete or mixed control); and (iii) geographically concentrated ethnic minorities face a higher risk of violence. © 2012 Wiley Periodicals, Inc. Complexity 17: 42–51, 2012

Key Words: ethnic geography; violence; agent-based modeling; Afghanistan

INTRODUCTION

How does ethnic geography, the spatial distribution of individuals from nominally rival ethnic groups, shape violence in civil war? The literature posits three contradictory responses. Drawing on the concept of a security dilemma, Melander contends that ethnic diversity, not concentration, entails a higher risk of warfare given greater first-strike advantages, when rival groups are interspersed compared to when they are segregated [1]. In contrast, Toft advances the notion that a concentrated ethnic group is most prone to rebellion—the rationale being that geographic concentration increases territorial attachment and facilitates group mobilization for conflict by alleviating collective action problems, the latter finding supported by Weidmann [2, 3]. And lying squarely in between these poles, Lim et al. suggest that conflict is most likely to occur in areas where group concentration is sufficiently large to impose cultural norms but insufficiently large to enable the formation of self-sufficient entities—the gray area between concentration and mixing containing groups of a given characteristic size [4], p 1542. Related scholarship examines the impact of territorial control on violence and ethnic defection [5, 6], intrainsurgent rivalry and fratricide as a motive for ethnic defection [7], how the

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political exclusion of powerful ethnic groups and their distance from the capital shapes territorial conflict \cite{8,9}, and the effect of local population clusters on the location of conflict events \cite{10, 11}.

**OUR CONTRIBUTION**

In line with the rich and rapidly developing literature on geography and conflict, we subscribe to the view \cite{12–15} that the use of country aggregates, whether as proxies for ethnicity or conflict, obscures space-varying factors at a disaggregated or subnational level. Yet, in examining how ethnic geography—the mixing or concentration of individuals from nominally rival ethnic groups—shapes the distribution of violence in civil war, our analysis departs from this body of work in notable respects.

We model the relationship between ethnic geography and violence at the subnational level paying particular attention to how the distribution of ethnic groups shapes territorial control, patterns of collaboration, and violence against civilians. Such a mechanism either remains unaddressed \cite{16–20, but see 21} or relegated to the background \cite{4} in previous, otherwise noteworthy, computational frameworks. Accordingly, in constructing and calibrating our model, we utilize disaggregated data on the geographic location of ethnic groups in Afghanistan and the location of violence.

Our analysis proceeds in three stages. First, we seed the calibrated model. Our findings suggest that (i) political actors are more likely to attack civilians in heterogeneous areas where members of one ethnic group are exposed to members of a rival group; (ii) violence directed at civilians occurs with greater frequency in locations where one political actor exercises hegemonic but incomplete territorial control; and (iii) geographically concentrated ethnic minorities face a higher risk of violence. In a final step, we conduct counterfactual exercises to analyze how changes in ethnic settlement patterns alter the distribution of violence. We turn next to a specification of our computational framework.

**MODELING IRREGULAR WARFARE**

The model contains two agent types, civilians and political actors, with simple attributes and behavioral rules local to their environment. The model landscape consists of 3207 cells that reflect ethnic settlement patterns in Afghanistan, based on data from the geo-referencing of ethnic groups (GREG project \cite{23}). Each cell is inhabited by civilians who belong to one of the following ethnic groups—Pashtuns, Tajiks, Hazaras, Uzbeks, and a residual ‘other’ category. The population of each cell is estimated by a geographic information systems (GIS) raster dataset \cite{24} with a scale of 1:200. Two rival political actors—pro-Taliban forces and pro-U.S.-led coalition forces—fight to expand territorial control over the landscape. We assume that Pashtuns are politically affiliated with pro-Taliban forces, whereas Tajiks, Hazaras, and Uzbeks are affiliated with pro-U.S. led coalition forces.

Each civilian is characterized by four core attributes: an ethnic identity \(e\) denoting membership in and distance between ethnic groups; ethnic salience \(s\) where \(m_e\) denotes the weight placed on ethnicity as a core or defining identity; a character \(c\) randomly distributed on the unit interval to denote some arbitrary set of personal preferences; and a propensity for risk taking \(r\) (Table 1 for parameter ranges). The degree of local rivalry between a given pair of civilians is then based on interpersonal differences in ethnic identity and character—with the former outweighing the latter as ethnic salience increases. The greater the interpersonal distance, the higher the satisfaction derived from the elimination of a rival. In addition to these attributes, civilians have a vision \(s\) locally defined on a Moore neighborhood, and a threshold for denunciation \(\tau\).

Each political actor is defined by four core attributes: military capacity \(m^a\); logistical capacity \(l^a\); the distance from the current location to its stronghold \(d^a\); and vision with radius \(v^a\). In line with Boulding’s loss-of-strength gradient \cite{25}, we assume that military costs increase with the distance to an actor’s stronghold, given logistical obstacles, and the limited knowledge of the local populace and terrain. The effect of \(d^a\) nonetheless depends on the level of logistical capacity; that is, actors with high capacity may...

\footnotesize

1Although the ACLED dataset relies only on secondary sources, primarily local and regional news sources, and covers only a limited period of time in Afghanistan (January 2008–August 2009), it provides geo-referenced data on conflict events, including violence against civilians.
We assume that $d^*(a)$ given cell is calculated as a function of military capacity $m$. The probability of control this actor exercises over Two rival political actors compete for territorial control. Play unfolds in two successive stages: control and violence. Stage 1: Control Two rival political actors compete for territorial control. Each political actor is assigned a location to represent its stronghold, as well as a random chance of being the first mover. The probability of control this actor exercises over a given cell is calculated as a function of military capacity ($m^*$), logistical capacity ($l^*$), the distance to its stronghold ($d^*$), and the ethnic configuration of the location measured by the number of civilians from politically affiliated (or unaffiliated) electoral groups, together with the salience placed by group members on ethnicity ($s$). This probability is given by

$$p(\text{control}) = 1 - \exp(-5m^* \cdot \zeta \cdot \varphi)$$

where $\zeta = l^*/(l^* - 1) + d^*/(1 - l^*)$ and $\varphi = 0.5 + \mu_s \cdot \ln(a + 1) - \mu_u \cdot \ln(-a + 1)/k$. Both $\zeta$ and $\varphi$ range from 0 to 1, with higher values indicating higher probabilities of control. The key intuition behind these equations is straightforward: the value of $\zeta$ tends toward 1 as political actors possess high logistical capacities and/or are in locations close to their strongholds; the value of $\varphi$ approaches 1 as the number of politically affiliated (or unaffiliated) civilians, with high levels of ethnic salience, increases (or decreases).

We make the following simplifying assumptions in stage 1: (i) the presence of friendly ethnic groups gives political actors a strategic advantage and lowers the cost of territorial control; (ii) rival actors begin by controlling cells within $d^* = 1$ and $d^*$ increases by 1 in each subsequent round of play; and (iii) the military cost of control increases as actors seek to capture cells further from their strongholds. We run stage 1 until every cell is controlled by a political actor, with the end result that zones (a collection of contiguous cells within a grid of a given size) in the landscape may be “jointly” controlled by both actors, “incompletely” controlled by either or “completely” controlled by a single actor [Figure 1(C)]. After freezing the scenario with respect to territorial control, the simulation proceeds to the next stage.

Stage 2: Violence Stage 2 is run for the requisite number of time steps (to achieve similarity between the numbers of observed and simulated locations of violence) with the following behavioral rules for civilians and political actors.3

**Civilian Behavior**4

Civilians collaborate with political actors and denounce their neighbors based on two simple rules. Initially, each civilian counts the proportion of cells controlled by Taliban $\pi_T$ and the proportion controlled by coalition forces $\pi_C$ within $\nu$ and collaborates with the dominant political actor based on the following rule5:

**Rule 1:** Within $\nu$, if $\pi_T \geq 0.6$, then collaborate with the Taliban; if $\pi_C \geq 0.6$, then collaborate with the coalition forces; else remain neutral.

The second rule specifies the conditions under which a civilian will denounce another civilian (a local rival) to the political actor with whom she collaborates. We define civilian $i$’s satisfaction derived from the elimination of a local

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### Table 1

<table>
<thead>
<tr>
<th>Model Parameters</th>
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<tbody>
<tr>
<td><strong>Agent-level parameters</strong></td>
</tr>
<tr>
<td>c</td>
</tr>
<tr>
<td>s</td>
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<tr>
<td>r</td>
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<tr>
<td><strong>Group-level parameters</strong></td>
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<tr>
<td>e</td>
</tr>
<tr>
<td>m*</td>
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<tr>
<td>l*</td>
</tr>
<tr>
<td>v*</td>
</tr>
<tr>
<td>v</td>
</tr>
<tr>
<td><strong>Global parameters</strong></td>
</tr>
<tr>
<td>$\tau$</td>
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<tr>
<td>$p$</td>
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</tbody>
</table>

Logistic capacity ($l^*$) ranges from 50 to 100 to denote the maximum distance that a political actor can reach from its stronghold.
rival \( j \) by \( \delta = s_i | e_j - e_j | + (1 - s_i) | c_j - c_j | \) or a convex combination of the absolute values of the difference between ethnic identities and characters. We define \( i \)'s safety from retaliation by denouncer \( j \)'s family (\( \sigma \)) as the proportion of cells controlled by the political actor with whom she collaborates within \( \nu \). Net risk is defined as \( 1 - (r_i \cdot \sigma) \), the product of risk-taking propensity and safety. A civilian's utility from denouncing another civilian is then given by:

\[
u(\text{denounce}) = [\delta + (r_j \cdot \sigma) - 1]
\]

**Rule 2:** Within \( \nu \), a civilian will denounce another civilian iff \( u(\text{denounce}) > \tau \).

**Political Actor Behavior**

When a denouncer is observed, political actors assassinate him iff at least one civilian collaborates with the rival political actor within a locality:

\[
u(\text{denounce}) = [\delta + (r_j \cdot \sigma) - 1]
\]

**Rule 3:** Within \( \nu^* \), detect a denounced civilian and assassinate her given the presence of an enemy collaborator.

**Endogenizing Salience**

In addition to the basic rules described above, we endogenize ethnic salience as increasing (or decreasing) with the proportion of cells that experience interethnic \( \pi_{\text{ethnic}} \) or intraethnic \( \pi_{\text{intra}} \) violence within \( \nu \). We also include a parameter to reflect the possibility that civilians mistakenly perceive interethnic (or intraethnic) violence as intraethnic (or interethnic) with probability \( p \). That is,

\[
u(\text{denounce}) = [\delta + (r_j \cdot \sigma) - 1]
\]

**MODEL INITIALIZATION AND CALIBRATION**

We calibrate our model in NetLogo (v. 4.0). Empirical data on the observed locations of violence in Afghanistan—a total of 379 geo-referenced events of violence against
civilians between January 2008 and August 2009—is obtained from ACLED. Model calibration consists of the following steps: (i) 170 square grids are overlaid on the model landscape with a resolution of 61.5 × 61.5 km (Figure 2); (ii) we take the average number of violent locations within each grid block from 300 independent model runs for the set of parameter vectors \(\{s, m^*, \beta, \alpha, \gamma, p\}\); (iii) we normalize this number to the total number of violent locations in all grid blocks; (iv) we calculate the sum of squared differences (SSD) between the normalized number of observed and simulated locations of violence across the 170 grid blocks; and (v) we repeat steps (ii)–(iv) for all possible parameter vectors. We base our analysis on the vector that minimizes SSD (the minimum value of SSD obtained in these experiments is 0.0231 and the maximum is 0.1042) and report calibrated values of the five model parameters in Table 2.7

The goodness-of-fit between the observed locations and the simulated output based on binary indicators for each grid block (which equal 1 if one or more violent location is present and equal 0 otherwise) is 70.76%, which could plausibly be improved with more refined measures of Afghanistan’s ethnic geography.8 A ‘chance-adjusted’ kappa index of 0.412 \((p < 0.00)\) nonetheless indicates ‘moderate’ agreement between the observed and predicted locations of violence [Figure 1(D)].

**SIMULATION RESULTS**

With confidence in our model’s predictive power, we fit a logistic regression model to the simulated data. This approach has two principal advantages. First, it enables us to assess the effect of “territorial control,” a key intervening variable linking ethnic geography to violence in the model. Reliable information on territorial control is not readily available in empirical data. Second, it permits us to compare our baseline results to those derived from counterfactual analyses in which the model’s ethnic geography is altered.

Units of observations in our experiments consist of 170 square grids overlaid on the model landscape. We utilize a dichotomous-dependent variable to denote whether a grid block contains, on average, one or more locations of violence after 300 independent model runs (values less than 1 are rounded down to 0). Our first independent variable (zone), also dichotomous, is coded 1 for grid blocks in zones 2 and 4, zones in which we expect to observe the highest levels of violence against civilians.10 Specifically, zones 2 and 4 are defined as grid blocks where the percentage of cells controlled by one of the political actors is between 20% and 40% or between 60% and 80%. Our second independent variable (exposure) measures the extent to which members of group X are exposed to members of group Y (26), p 288 within a block. This measure ranges from 0 to 1 and can be interpreted as the probability that a randomly drawn X-member shares a Moore neighborhood with a member of Y. Our third independent variable...
elf) is the level of ethnic fractionalization, or the probability that two randomly selected civilians in each block will not belong to the same ethnic group (either to X or to Y alone), and ranges from 0 to 1. We also calculate two indexes of spatial proximity (majcon and mincon) to capture the degree of ethnic concentration among members of the ethnic majority and minority, respectively. Ranging from 0 to 1, this index measures the average proximity between members of the same ethnic group [26], p 295). It approaches 1 as members of the same group live nearer to one another within a block. As such, we utilize the four indices to capture the impact that different dimensions of ethnic geography-exposure, fractionalization, and concentration-have on the location of violence. Lastly, we utilize logged population size (lnpop) as a control variable.

### TABLE 2

Calibrated Model Parameters

<table>
<thead>
<tr>
<th></th>
<th>s</th>
<th>m*</th>
<th>f*</th>
<th>v*</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ethnic salience</td>
<td>s ~ N [0.4, 0.15]</td>
<td>0.7</td>
<td>70</td>
<td>3.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Military capacity</td>
<td>m*: Taliban; 0.9: coalition forces</td>
<td>0.9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logistic capacity</td>
<td>f*: Taliban; 80: coalition forces</td>
<td>80</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vision (political actors)</td>
<td>v*: Taliban; 2.5: coalition forces</td>
<td>2.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Probability of misperception</td>
<td>p: 0.1</td>
<td></td>
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</tbody>
</table>

Denunciation threshold (s) was held constant at 0.3 in all model runs to achieve similarity between the numbers of observed and simulated locations of violence. Setting s to different values produces either too many or too few locations of violence than reported in the ACLED dataset.

### TABLE 3

Logistic Analyses of Simulated Data

<table>
<thead>
<tr>
<th></th>
<th>Counterfactual (Highly Segregated)</th>
<th>Counterfactual (Partially Segregated)</th>
<th>Counterfactual (Highly Mixed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zone</td>
<td>Zone</td>
<td>Zone</td>
<td>Zone</td>
</tr>
<tr>
<td>Exposure</td>
<td>Exposure</td>
<td>Exposure</td>
<td>Exposure</td>
</tr>
<tr>
<td>Majcon</td>
<td>Majcon</td>
<td>Majcon</td>
<td>Majcon</td>
</tr>
<tr>
<td>Mincon</td>
<td>Mincon</td>
<td>Mincon</td>
<td>Mincon</td>
</tr>
<tr>
<td>Lnpop</td>
<td>Lnpop</td>
<td>Lnpop</td>
<td>Lnpop</td>
</tr>
<tr>
<td>Constant</td>
<td>Constant</td>
<td>Constant</td>
<td>Constant</td>
</tr>
<tr>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
</tr>
</tbody>
</table>

Standard errors and p values in parentheses.

* p < 0.05 (two-tailed test).
** p < 0.01 (two-tailed test).
*** p < 0.001 (two-tailed test).
Results from models 1 and 2 (Table 3) indicate that areas with greater levels of ethnic exposure and fractionalization are more likely to experience violence. For changes in exposure and elf from their 25th to 75th percentile values, the predicted probability of violence increases by an average of 0.252 and 0.309, respectively, holding zone at 0 and all other variables at their means. Higher levels of ethnic minority concentration also increase the probability of violence ($p < 0.01$). In model 1, a change in mincon from its 25th to 75th percentile value results in a change of 0.113 in the predicted probability of violence, holding zone at 0 and all other variables at their means. In addition, violence is more likely to occur in areas incompletely controlled by political actors (zones 2 and 4) in comparison to zones of mixed and complete control (zones 1, 3, and 5). The probability of violence increases by 0.411 on average as zone goes from 0 to 1, holding all other variables at their means. The coefficients for ethnic majority concentration (majcon) have negative signs but are not statistically significant in both models. These results are graphically displayed in Figure 3.

**COUNTERFACTUAL ANALYSIS**

Next, we conduct a set of counterfactual exercises to analyze how the spatial distribution of violence shifts with changes in ethnic geography. To do so, we create three hypothetical ethnic landscapes—highly segregated, partially segregated, and highly mixed—while keeping the number of ethnic groups and population density as constant (Figure 4). We run our model on the three landscapes using the same parameter values reported in Table 2.
Again, results from the counterfactual experiments are based on the average number of casualties within each grid block taken from 300 independent model runs. Logistic analyses of the simulated data, models 3–8, are reported in Table 3.

Results from models 3 and 4 suggest that violence is more likely to occur in areas with greater degrees of ethnic exposure and fractionalization (elf) in a highly segregated environment ($p < 0.01$ for both). The coefficients for ethnic minority concentration (mincon) also have positive signs and are significant in model 3 ($p < 0.01$) alone. However, the coefficients for zones of incomplete control (zone) lose their significance in both models 3 and 4, suggesting that territorial control does not contribute to greater probability of violence in an extremely segregated environment. In a highly mixed environment, however, the coefficients for zone assume significance ($p < 0.01$ in models 7 and 8), with a unit change in zone increasing the probability of violence by 0.033 on average, holding all other variables at their means. The coefficients for exposure, elf, and mincon, however, lose their significance in both models 7 and 8, suggesting that territorial control plays a more important, albeit modest, role than ‘ethnic geography’ when a high level of mixing occurs.

On the other hand, the effects of ethnic geography are especially pronounced in a partially segregated environment. Figure 5 displays the probability of violence for highly (model 3) and partially (model 5) segregated landscapes as a function of exposure. In both cases, the probability of violence increases with exposure (or fractionalization) albeit far more significant in the partially segregated environment. In model 5, the probability of violence increases by 0.387 on average as exposure changes from its 25th to 75th percentile value, holding zone at 0 and other variables at their means. The same change in exposure increases the probability of violence by only 0.106 in model 3.

CONCLUSIONS
How does ethnic geography shape violence in civil war? Our simulation using Afghanistan’s ethnic landscape points to the role of hegemonic but incomplete territorial control, ethnic heterogeneity—higher degrees of ethnic fractionalization or exposure—and the presence of concentrated ethnic minority as key explanatory factors. Yet, our counterfactual experiments using stylized ethnic landscapes—highly segregated, partially segregated, and highly mixed—suggest a more nuanced perspective. A high level of ethnic segregation raises the importance of exposure, fractionalization, and minority concentration as predictors of violence relative to territorial control, whereas the reverse appears to hold given a high level of ethnic mixing. Our experiments further indicate that the probability of violence against civilians increases with ethnic exposure or fractionalization far more significantly in a partially, relative to a fully segregated environment. Surprisingly, we find little support for the role of a concentrated ethnic majority in explaining the incidence of violence, running against the grain of previous findings [2, 3, 27]. Overall, our findings suggest that civil war onset and violence during civil war are likely to be associated with the spatial distribution of ethnic groups in different ways. Although geographically concentrated ethnic majority groups seem most prone to initiating conflict,
actual violence during civil war appears more likely in ethnically diverse areas. As a plausible next step, the analysis of multicity data on ethnic geography and violence could be used to assess the validity of these new findings.

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