Predicting the Evolution of Intrastate Conflict: Evidence from Nigeria ☆

Cassy Dorff[1], Max Gallop[b], Shahryar Minhas[c]

[a]*Department of Political Science, University of New Mexico, Albuquerque, NM 87106, USA*
[b]*University of Strathclyde, Glasgow, 16 Richmond St., Glasgow, UK G1 1XQ*
[c]*Department of Political Science, Duke University, Durham, NC 27701, USA*

Abstract

The endogenous nature of civil conflict processes have limited scholars' abilities to draw clear inferences about key drivers of conflict evolution. Using ACLED event data, we apply a new network-based approach to trace the evolution of intra-state conflict dynamics and test how the behavior of violent actors push armed groups closer together or further apart over time. For example, we examine whether violence against civilians isolates groups from one another, or increases the probability of violence between them. This dynamic network allows us to estimate the relationship between network position and the probability of a violent event. We then use this information to predict conflict in Nigeria using an out-of-sample design. We compare these predictions to those generated using both a standard structural model of intrastate conflict and a model assuming a static network.

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Email addresses: `cassy.dorff@unm.edu` (Cassy Dorff), `max.gallop@strath.ac.uk` (Max Gallop), `shahryar.minhas@duke.edu` (Shahryar Minhas)

Introduction

Theory

The Conflict[s] in Nigeria

ACLED Data

Creating a Conflict Network in Nigeria

Modelling Approach

To model and predict intra-state conflict in Nigeria, we rely on an Additive and Multiplicative Effects (AME) model. This is a model that can account for many of the interdependencies in relational data. The particular estimator is:

$$Y_{ijt} = g(\mathbf{X_{ijt}^T}\beta + a_i + b_j + \mathbf{u_i}\delta\mathbf{v_j} + \epsilon_{ijt}) \tag{1}$$

where Y_{ijt} represents the amount of conflict between actor i and actor j at time t. The additive part of the model is derived from **?**'s Social Relations Regression Model, and is composed of the fixed effects $\mathbf{X_{ijt}^T}\beta$ which account for (potentially time varying) covariates in the model, as well as the sender and receiver effects a_i and b_j. The random effects account for one source of interdependency in relational data: the tendency for certain actors to be disproportionately involved in conflict. The stochastic error ϵ_{ijt} is defined as:

$$e_{ijt}\text{+}iid \sim N(0, \Sigma_\epsilon) \tag{2}$$

$$\Sigma_\epsilon = \sigma_\epsilon \begin{pmatrix} 1\rho \\ \rho 1 \end{pmatrix} \tag{3}$$

where ρ is a measure of reciprocity in the data. These factors allow us to take into account the similarity between ij interactions and ji interactions. However, while additive effects can deal with first (differing popularity and activity of actors) and second order interdependencies (reciprocity), the multiplicative effects are needed to deal with third order dependencies. Two third-order dependencies worth considering here are homophily – the tendency of actors with similar characteristics are more likely to form strong relationships than those with differing characteristics – and stochastic equivalence, the possibility that two actors i and j will have similar relationships with every other actor in the network. An AME model accounts for these third order effects using the multiplicative term $\mathbf{u_i}\delta\mathbf{v_j}$. This model posits a latent vector of characteristics $\mathbf{u_i}$ and $\mathbf{v_j}$ for each sender i and receiver j. The similarity or dissimilarity of these vectors will then influence the likelihood of activity, and therefore account for these third order interdepencies (**?**).

0.1. Latent Factors

An important thing to understand the latent factor model here is that it is different than a latent space model as traditionally used. Even though, in the models discussed, the latent factor has two dimensions, and we can thus plot it, the Euclidian distance between the different actors is not easily interpretable. Rather that looking at distance, we should look at the direction of the factors for the actors. If we represent the latent factors as vectors, than actors who have these vectors in the same direction will exhibit more stochastic equivalence, and those with actors in opposite directions will exhibit little such equivalence. In other words, if the factors point in the same direction, we should expect to see the actors having similar types and amounts of interactions with similar third parties.

We can get a sense of the direction of these factors by placing each actor on a unit circle based on direction of this vector in comparison to the center of each actor's positions. Then, we can get a measure of this stochastic equivalence by comparing the difference in angles between these two actors. We do this in section **??** to examine the effect of violence against civilians on the shape of the latent group network.

Variables

Results

Parameter Estimates

Network Dependencies

Out of Sample Performance Analysis

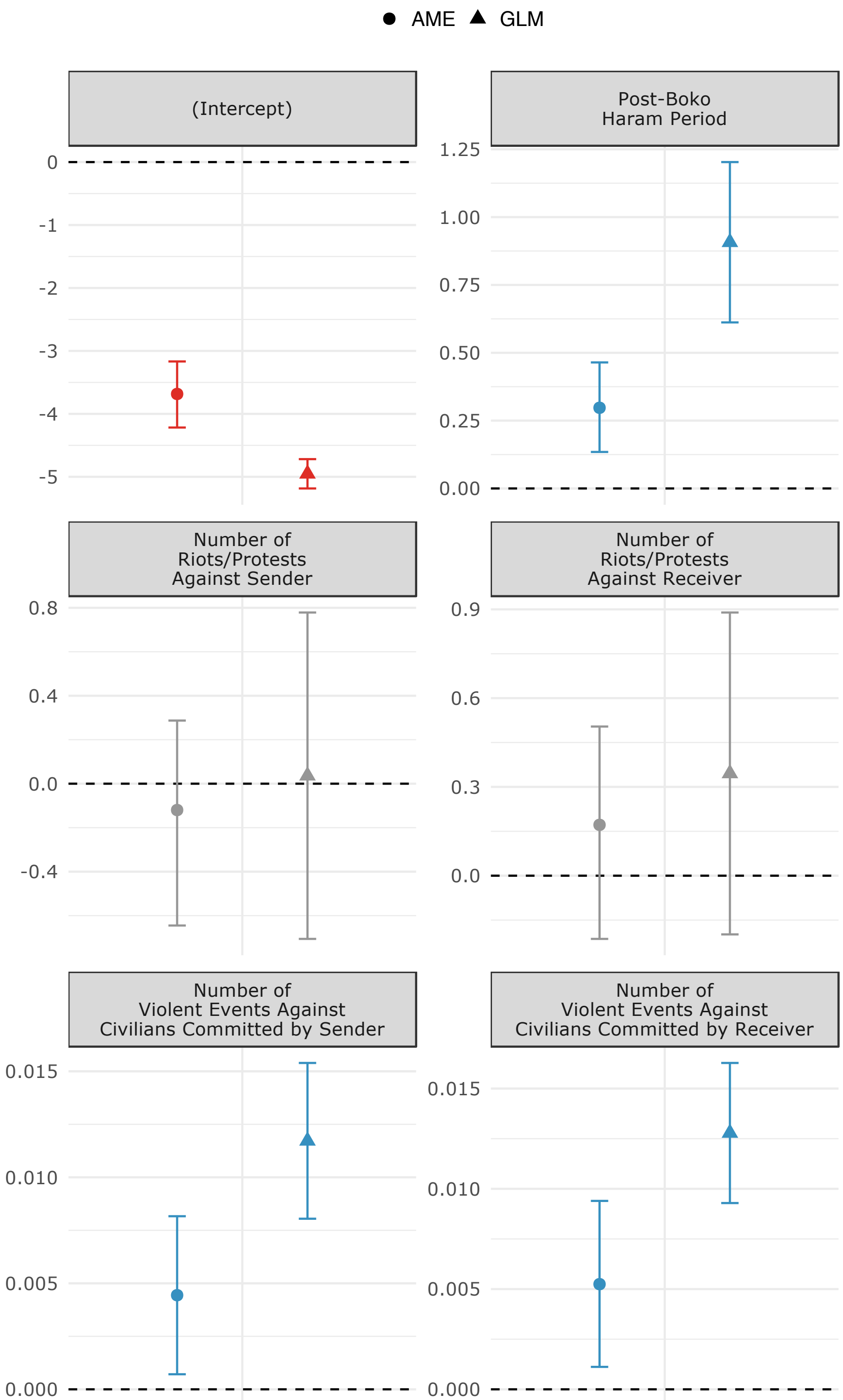

Figure 1: Exogenous parameter estimates from GLM and AME.

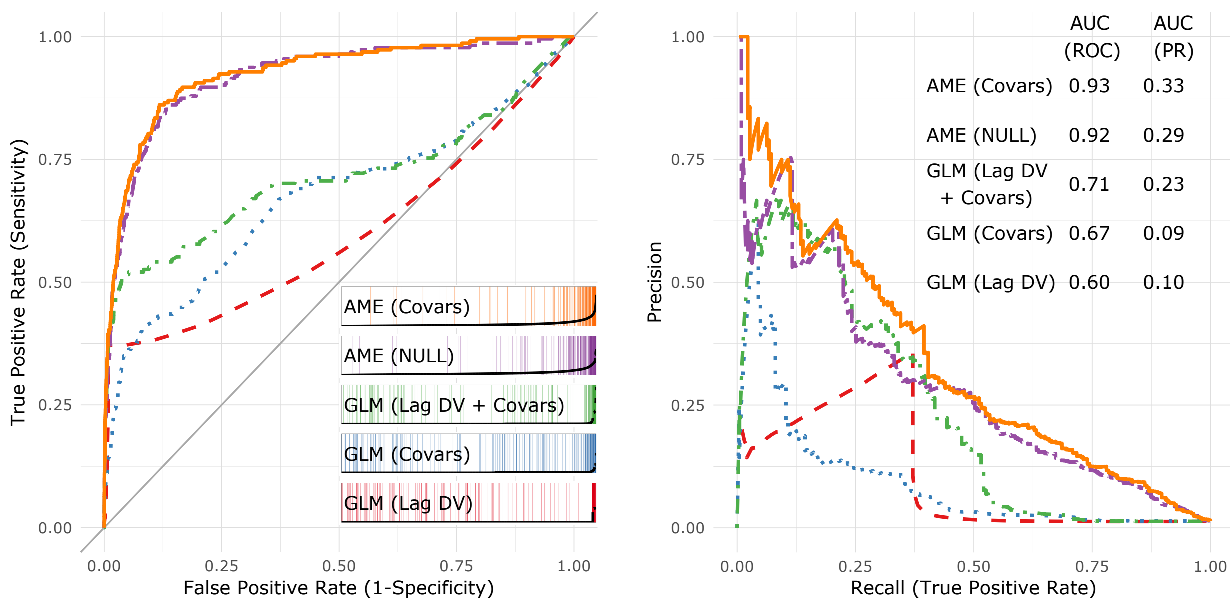

Figure 2: Assessments of out-of-sample predictive performance using ROC curves, separation plots, and PR curves. AUC statistics are provided as well for both curves.

Conclusion

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