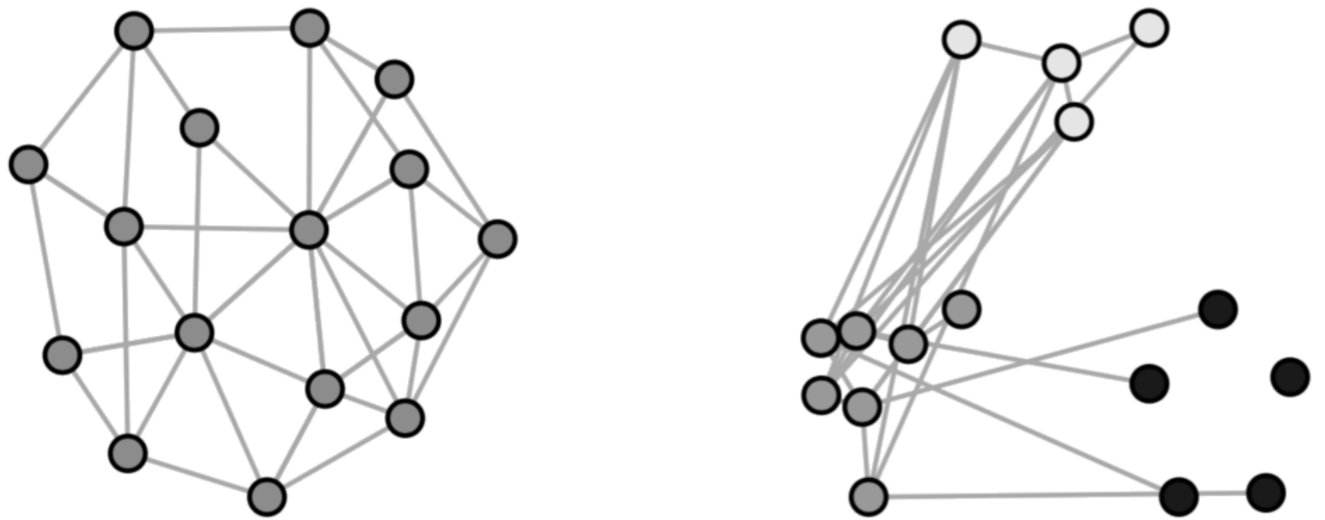
What are we missing?



- **Homophily**: "birds of a feather flock together"
- **Stochastic equivalence**: nothing as pithy to say here, but this model focuses on identifying actors with similar roles

Now we'll start to build on what we have so far and find an expression for γ:

$$y_{ij} \approx \beta^T X_{ij} + a_i + b_j + \gamma(u_i, v_j)$$

How nodal variables shape dyadic relations

Lets say that we are interested in predicting conflict or trade, we have all sorts of nodal based explanations for why some countries are less likely to engage in conflict or trade.

But we also have theories about how the **combination** of nodal characteristics between a pair of countries may shape conflict or trade, meaning that there might be dyadic covariates we think matter which are simply a function of nodal covariates, for example:

- $joint\ democ_{ij} = f(democ_i, democ_j)$
- $common\ igos_{ij} = f(igo_i, igo_j)$
- $distance_{ij} = f(distance_i, distance_j)$

Nodal to dyadic

Lets take the idea of joint democracy since it's a prominent example in the IR literature.

Specifically the IR lit often argues that our expectations about the probability of conflict or level of trade changes as a function of joint democracy: $x_{i,j} = f(democ_i, democ_j)$, which suggests a model such as:

$$\begin{aligned} y_{i,j} &\sim \beta_0 + \beta_1 x_{i,j} \\ x_{i,j} &= \boldsymbol{s}(x_i, x_j), \end{aligned}$$

where $\boldsymbol{s}()$ is some non-additive function of nodal characteristics

Nodal to dyadic

More generally instead of writing out x lets use slightly different notation, let:

u_i be a covariate (i.e., an x) of i as a sender of ties v_j be a covariate of j as a receiver of ties

$$y_{i,j} \sim \beta_0 + \beta_1 \boldsymbol{s}(u_i, v_j)$$

With this kind of framework we can actually explain higher order patterns in network data such as transitivity and stochastic equivalence.

Homophily induces transitivity

Homophily is just the idea that similar nodes link to each other, and as Shalizi and Thomas (2010) and others note homophily leads to transitive or clustered social networks, lets see what this implies for our simple example:

$$y_{i,j} \sim \beta_0 + \beta_1 s(x_i, x_j)$$

Lets say that $\beta_1 > 0$, for our joint democracy example this is equivalent to saying that when two countries are both democracies (i.e., x_i and x_j = 1), we expect there to be higher values on our dependent variable.

For simplicity, lets imagine that y is a binary matrix, then:

- $y_{ij} = 1 \implies x_i \approx x_j$
- $y_{ik} = 1 \implies x_i \approx x_k$
- $x_i \approx x_j, \ x_i \approx x_k \implies x_j \approx x_k$
- $x_j \approx x_k \implies y_{jk} = 1$

What about finding nodes with "similar" roles

Stochastic equivalence is the idea that similar nodes have similar relational patterns, and as we discussed these similar nodes may or may not link to each other but the key is that similar nodes can be thought of as having the same type of role in the network

In our general example from the previous slides:

$$y_{i,j} \sim \beta_0 + \beta_1 \boldsymbol{s}(u_i, v_j)$$

If $u_i \approx u_k$ then nodes i and k are stochastically equivalent as **senders**

If $v_i \approx v_k$ then nodes i and k are stochastically equivalent as **receiver**

Latent factor model

Homophily and stochastic equivalence from unobserved variables can be represented as a latent factor model

$$y_{i,j} \sim u_i^T D v_j$$

- u_i is a vector of latent factors describing i as a sender of ties
- v_j is a vector of latent factors describing j as a receiver of ties
- D is a diagonal matrix of factor weights

Latent factor model

Estimation of the latent factors is similar to a singular value decomposition:

$$
\begin{aligned}
Z &= U^T DV + E \\
z_{ij} &= u_i^T D v_j + \epsilon_{ij} \\
&= \sum_{r=1}^{T} d_r u_{i,r} v_{j,r} + \epsilon_{ij}
\end{aligned}
$$

For example, if R is equal to 2 then we have:

$$z_{ij} = d_1(u_{i,1} \times v_{j,1}) + d_2(u_{i,2} \times v_{j,2}) + \epsilon_{ij}$$

Interpretation here is:

- $u_i \approx u_j$: similarity of latent factors implies approximate stochastic equivalence
- $u_i \approx v_j$: similarity of latent factors has implications for the probability of a tie and direction of effect depends on value of d
- Specifically, if d is positive that represents homophily and if negative then anti-homophily (aka, heterophily)

Latent Factor Model

Vector notation for rank 2 model in the previous slide was this:

$$z_{ij} = d_1(u_{i,1} \times v_{j,1}) + d_2(u_{i,2} \times v_{j,2}) + \epsilon_{ij}$$

We could also just have written up the version for a rank 1 model:

$$z_{ij} = d_1(u_{i,1} \times v_{j,1}) + \epsilon_{ij}$$

That might remind you of where we started!

$$y_{i,j} \sim \beta_0 + \beta_1 s(u_i, v_j)$$

Latent factor model

The symmetric case works out similarly (though the matrix decomposition approach in this case is based on an eigendecomposition scheme):

$$\begin{aligned} Z &= U^T \Lambda U + E \\ z_{ij} &= u_i^T \Lambda u_j + \epsilon_{ij} \\ &= \sum_{r=1}^{T} \lambda_r u_{i,r} u_{j,r} + \epsilon_{ij} \end{aligned}$$

And again in the case of a rank 2 model:

$$z_{ij} = \lambda_1 (u_{i,1} \times u_{j,1}) + \lambda_2 (u_{i,2} \times u_{j,2}) + \epsilon_{ij}$$

Interpretation in the symmetric case:

- $u_{ir} \approx u_{jr}$: similarity of latent factors implies approximate stochastic equivalence
- $\lambda_r > 0$: positive eigenvalues represent homophily
- $\lambda_r < 0$: negative eigenvalues represent anti-homophily

Latent factor model

(Hoff 2003; Hoff 2007; Minhas et al. 2018; Hoff 2018)

To summarize, each node i has an unknown latent factor

$$\mathbf{u}_i \in \mathbb{R}^k$$

The probability of a tie from i to j depends on their latent factors

$$\begin{aligned} Pr(Y_{ij} = 1 | \mathbf{u}_i, \mathbf{u}_j) =& \theta + \mathbf{u}_i^T \Lambda \mathbf{u}_j \text{ , where} \\ & \Lambda \text{ is a } K \times K \text{ diagonal matrix} \end{aligned}$$

- Can account for both stochastic equivalence and homophily
- Comes at the cost of harder to interpret multiplicative factors ... let's see what I mean

Software packages:

- CRAN: `amen` (Hoff et al. 2015)

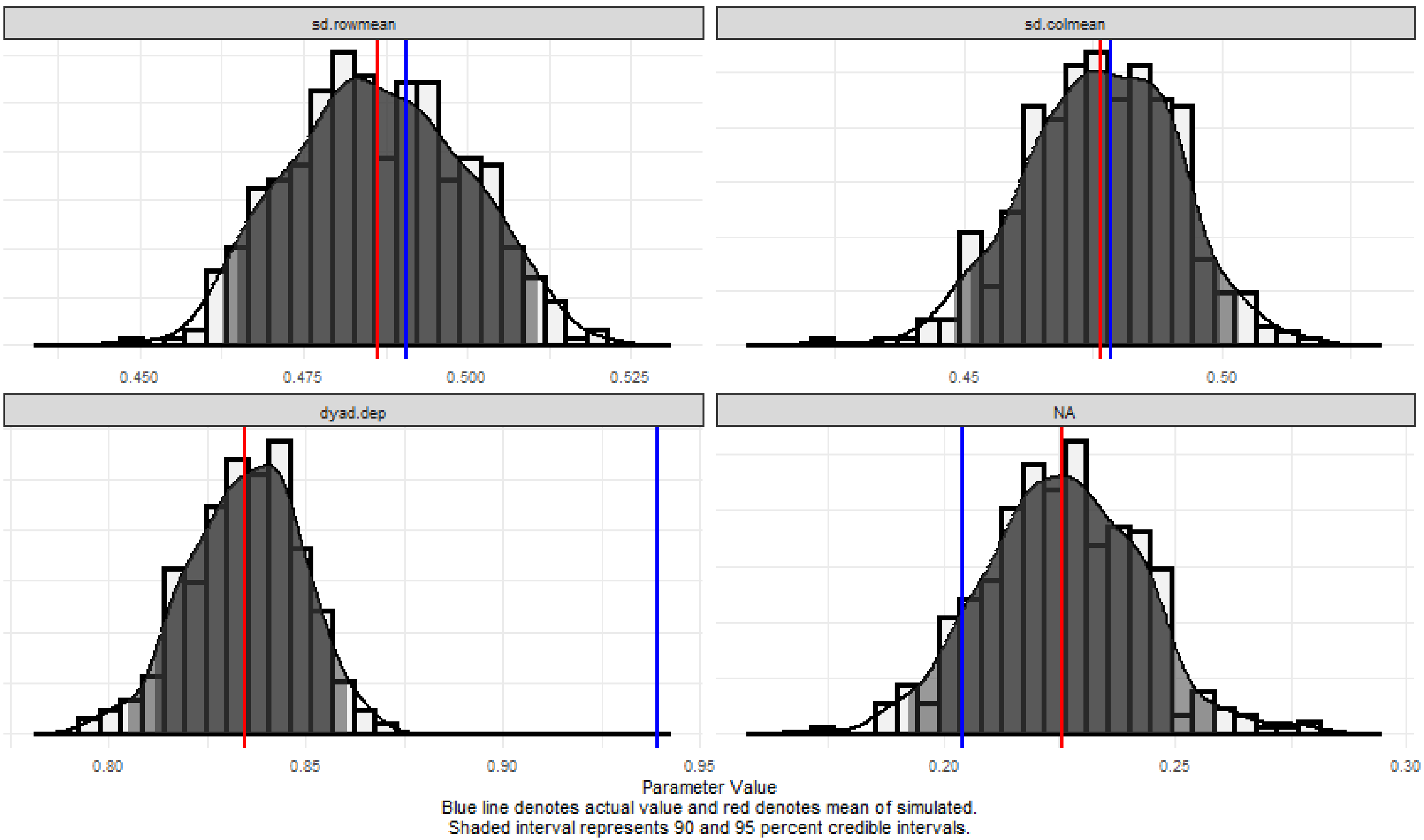
Running LFM through AME

To run a latent factor model, we can use the amen package again but this time we'll just restrict the estimated parameters as follows:

```
lfmFit = ame(Y,
  model='nrm', symmetric=FALSE,
  seed=6886,
  # restrict SRM parameters
  cvar=FALSE, rvar=FALSE, dcor=FALSE,
  R=2,
  plot=FALSE, print=FALSE
  )
```

How well do we capture network effects?

```
gofPlot(lfmFit$GOF, FALSE)
```



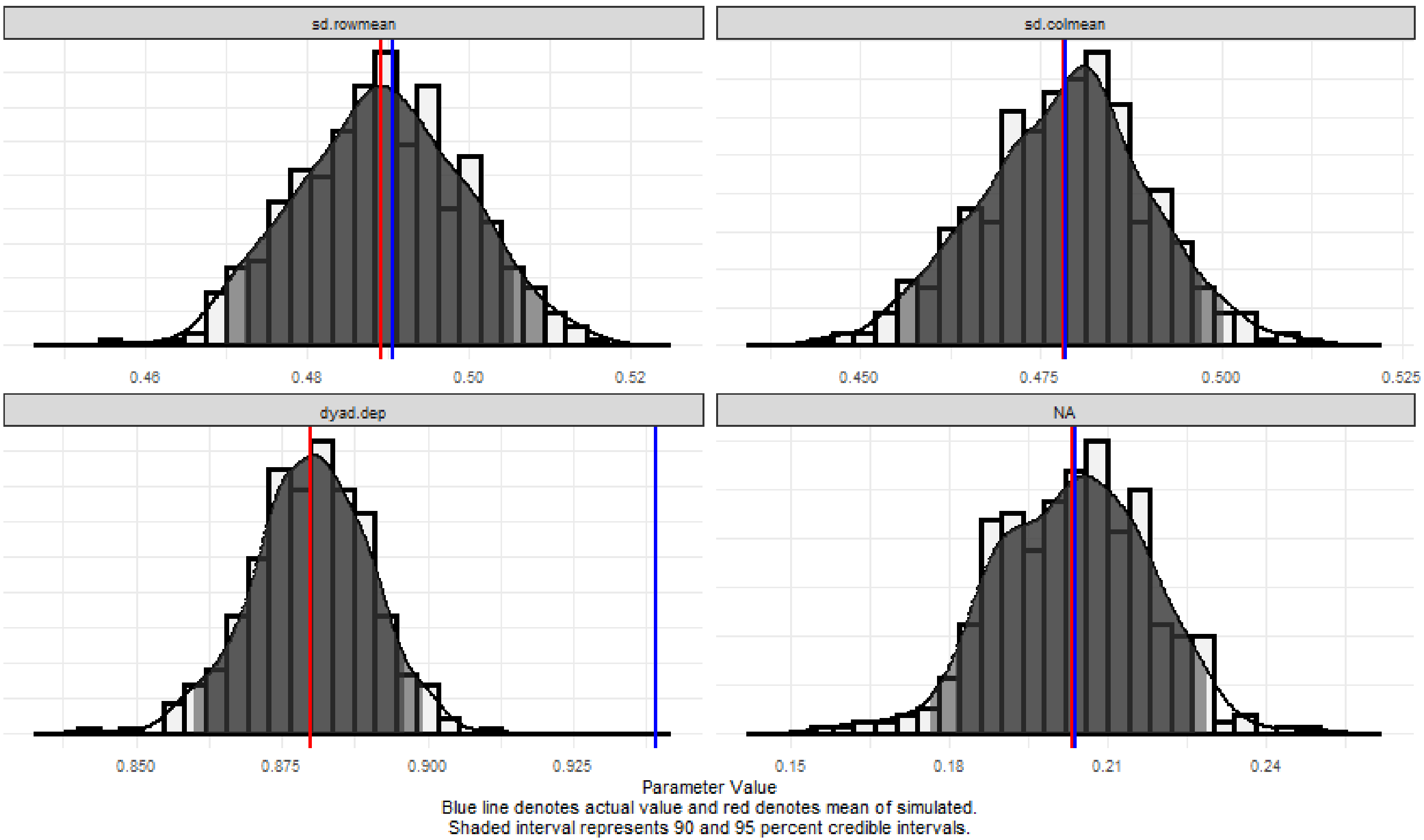
When to increase K

If our model is not adequately accounting for network effects, we can adjust the dimension of the multiplicative effects, R, in the LFM framework:

```
lfmFitk3 = ame(Y,
  model='nrm', symmetric=FALSE,
  seed=6886,
  cvar=FALSE, rvar=FALSE, dcor=FALSE,
  R=3,
  plot=FALSE, print=FALSE
  )
```

Check GOF again

```
gofPlot(lfmFitk3$GOF, FALSE)
```



Interpreting the UV term

So what is this UV term?

```r
lfmFitk3$U[1:3,]
```

```
##       [,1]   [,2]   [,3]
## ARG -0.349 -0.131 -0.046
## AUL -0.802 -0.124  0.634
## BEL -1.152 -0.083 -1.008
```

```r
lfmFitk3$V[1:3,]
```

```
##       [,1]  [,2]   [,3]
## ARG -0.405 0.246 -0.038
## AUL -0.819 0.321  0.397
## BEL -1.168 0.223 -0.981
```

```r
lfmFitk3$UVPM[1:3,1:3]
```

```
##       ARG   AUL   BEL
## ARG 0.112 0.226 0.423
## AUL 0.270 0.869 0.288
## BEL 0.485 0.516 2.317
```

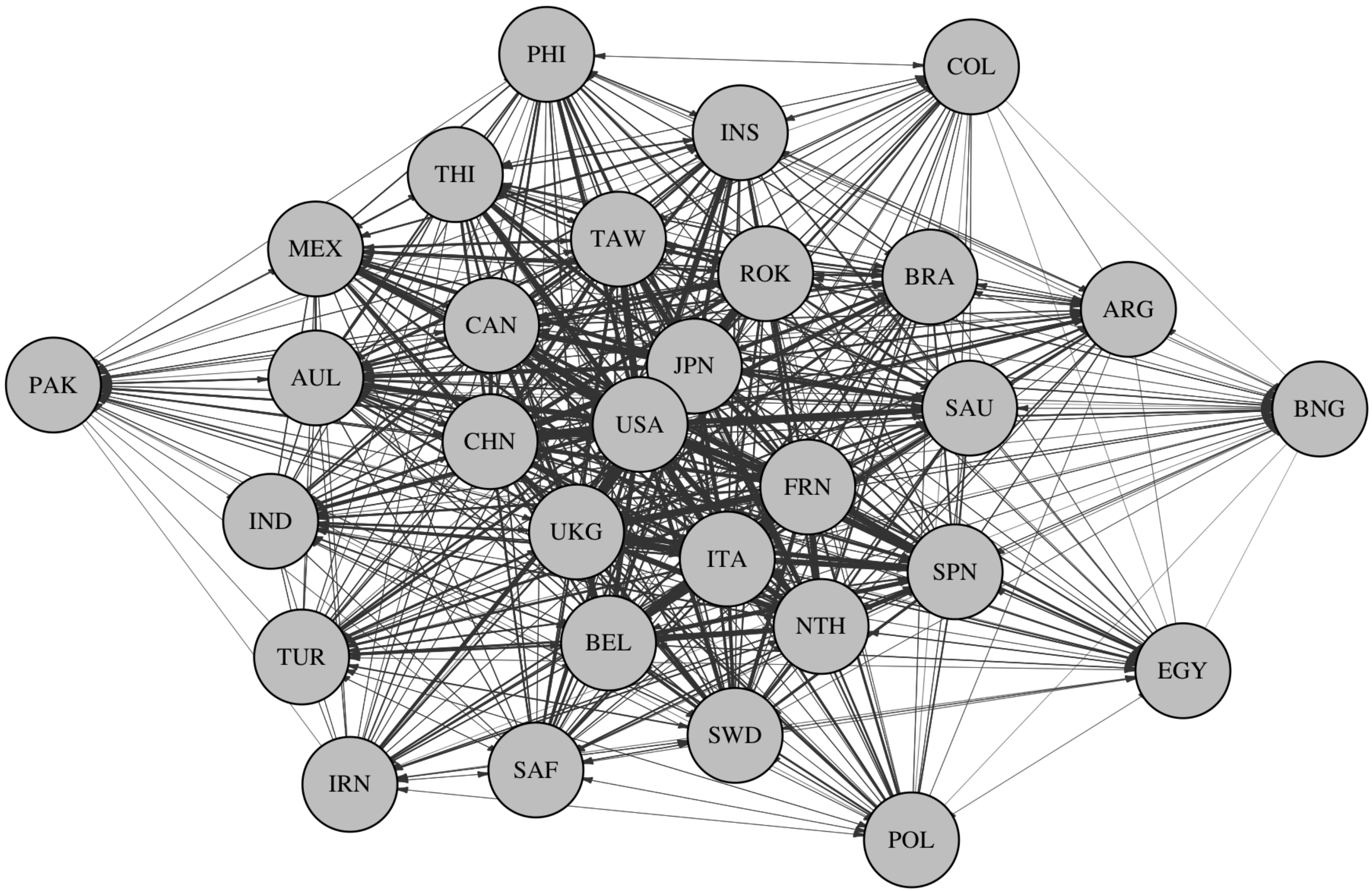
How can we use it?

We can interpret the cross-sections of the UV term as a measure of how likely a pair of actors are to form an edge with one another:

```
uv = lfmFit$UVPM ; diag(uv) = NA
uvNet = igraph::graph.adjacency(uv,
  mode='directed',
  weighted=TRUE,
  diag=FALSE)

set.seed(6886)
plot(uvNet,
  vertex.color='grey',
  vertex.label.color='black',
  vertex.size=V(yGraph)$size,
  vertex.label.cex =.75,
  edge.color='grey20',
  edge.width=E(uvNet)$weight,
  edge.arrow.size=.2,
  asp=FALSE
  )
```

Visualizing UVPM



Putting it all together: AME

$$
\begin{aligned}
y_{ij} &= g(\theta_{ij}) \\
\theta_{ij} &= \beta^T \mathbf{X}_{ij} + e_{ij} \\
e_{ij} &= a_i + b_j + \epsilon_{ij} + \mathbf{u}_i^T \mathbf{D} \mathbf{v}_j
\end{aligned}
$$

- $a_i + b_j + \epsilon_{ij}$, are additive random effects and account for sender, receiver, and within-dyad dependence
- multiplicative effects, $\mathbf{u}_i^T \mathbf{D} \mathbf{v}_j$, capture higher-order dependence patterns that are left over in θ after accounting for any known covariate information

AME Gibbs Sampler

- Probit regression framework: $y_{ij,t} = g(\theta_{ij,t})$, where $\theta_{ij,t} = \beta^\top \mathbf{X}_{ij,t} + a_i + b_j + \mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j + \epsilon_{ij}$
- Prior distributions for the parameters are specified as follows:
  - β drawn from multivariate normals with mean zero and a (0,10) covariance matrix
  - $\Sigma_{a,b} \sim$ inverse $\mathrm{Wishart}(I_{2\times 2}, 4)$
  - σ_u^2, and σ_v^2 are each drawn from an i.i.d. inverse gamma(1,1)

AME Gibbs Sampler

- Given initial values of $\{\beta, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho, \text{ and } \sigma_\epsilon^2\}$, the algorithm proceeds as follows:
  - sample $\theta \mid \beta, \mathbf{X}, \theta, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho, \text{ and } \sigma_\epsilon^2$ (Normal)
  - sample $\beta \mid \mathbf{X}, \theta, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho, \text{ and } \sigma_\epsilon^2$ (Normal)
  - sample $\mathbf{a}, \mathbf{b} \mid \beta, \mathbf{X}, \theta, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho, \text{ and } \sigma_\epsilon^2$ (Normal)
  - sample $\Sigma_{ab} \mid \beta, \mathbf{X}, \theta, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \rho, \text{ and } \sigma_\epsilon^2$ (Inverse-Wishart)
  - update ρ using a Metropolis-Hastings step with proposal $p^*|p \sim$ truncated normal${*[-1,1]*}*(\rho, \sigma*${\epsilon}^{2})$
  - sample $\sigma_\epsilon^2 \mid \beta, \mathbf{X}, \theta, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \text{ and } \rho$ (Inverse-Gamma)
  - For each $k \in K$:
  - Sample $\mathbf{U}_{[,k]} \mid \beta, \mathbf{X}, \theta, \mathbf{a}, \mathbf{b}, \mathbf{U}_{[,-k]}, \mathbf{V}, \Sigma_{ab}, \rho, \text{ and } \sigma_\epsilon^2$ (Normal)
  - Sample $\mathbf{V}_{[,k]} \mid \beta, \mathbf{X}, \theta, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}_{[,-k]}, \Sigma_{ab}, \rho, \text{ and } \sigma_\epsilon^2$ (Normal)
  - Sample $\mathbf{D}_{[k,k]} \mid \beta, \mathbf{X}, \theta, \mathbf{a}, \mathbf{b}, \mathbf{U}, \mathbf{V}, \Sigma_{ab}, \rho, \text{ and } \sigma_\epsilon^2$ (Normal)

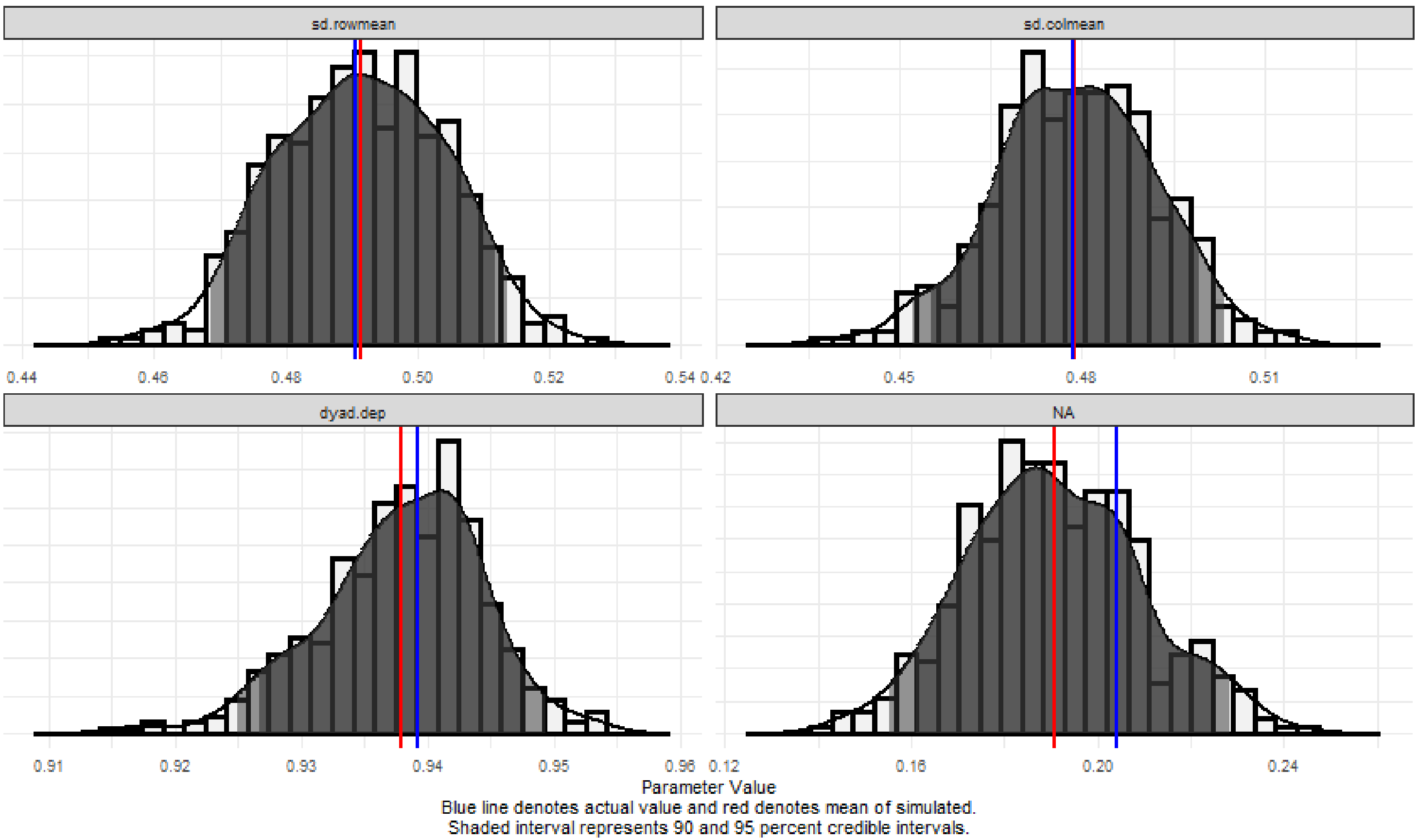
Estimating with multiplicative effects

Multiplicative effects can be added by toggling the `R` input parameter

```
fitAME = ame(Y=Y,
  Xdyad=Xd, # incorp dyadic covariates
  Xrow=Xn, # incorp sender covariates
  Xcol=Xcol, # incorp receiver covariates
  symmetric=FALSE, # tell AME trade is directed
  intercept=TRUE, # add an intercept
  model='nrm', # model type
  rvar=TRUE, # sender random effects (a)
  cvar=TRUE, # receiver random effects (b)
  dcor=TRUE, # dyadic correlation
  R=2, # 2 dimensional multiplicative effects
  nscan=10000, burn=25, odens=25,
  plot=FALSE, print=FALSE, gof=TRUE
  )
```

Capturing network features part 2

```
gofPlot(fitAME$GOF, symmetric=FALSE)
```

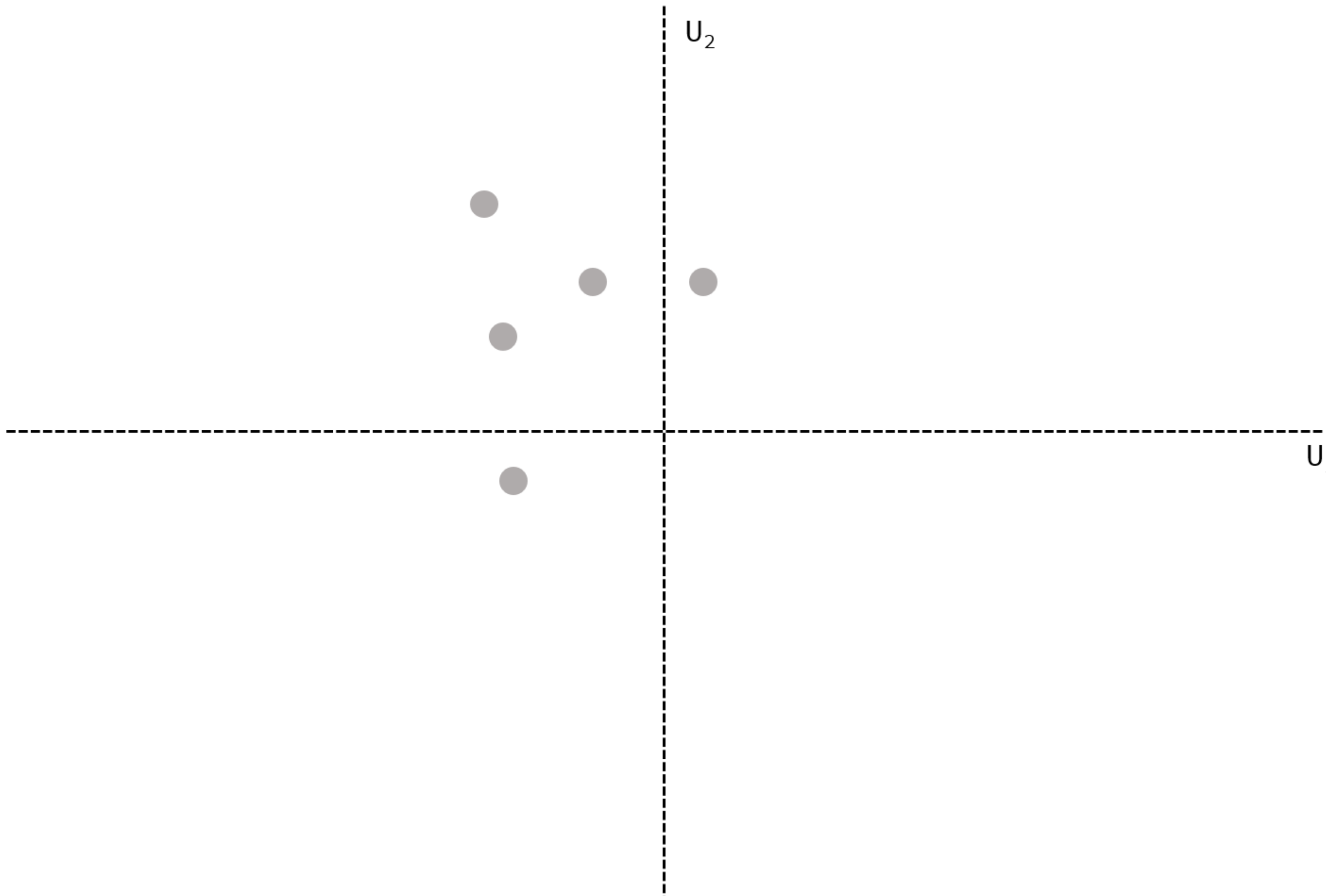


Summary method

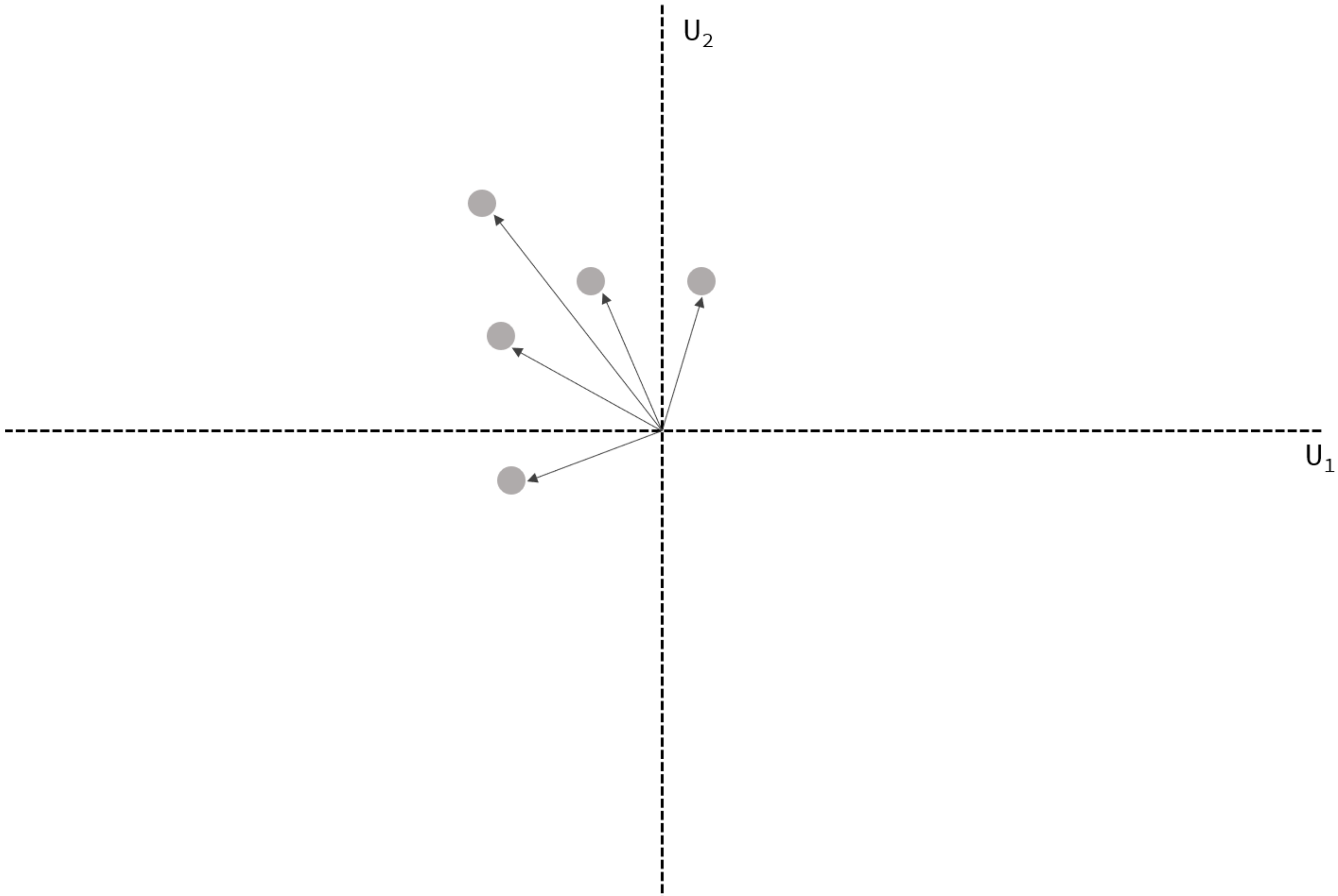
```
summary(fitAME)
```

```
##
## Regression coefficients:
##                     pmean   psd z-stat p-val
## intercept          -4.012 0.725 -5.530 0.000
## pop.row            -0.285 0.072 -3.948 0.000
## gdp.row             0.573 0.094  6.071 0.000
## polity.row         -0.006 0.012 -0.558 0.577
## pop.col            -0.245 0.073 -3.384 0.001
## gdp.col             0.530 0.094  5.625 0.000
## polity.col          0.001 0.011  0.086 0.932
## conflicts.dyad      0.018 0.038  0.477 0.634
## distance.dyad      -0.039 0.004 -8.907 0.000
## shared_igos.dyad  0.074 0.088  0.837 0.402
##
## Variance parameters:
##     pmean   psd
## va  0.073 0.022
## cab 0.029 0.017
## vb  0.069 0.019
## rho 0.626 0.037
```

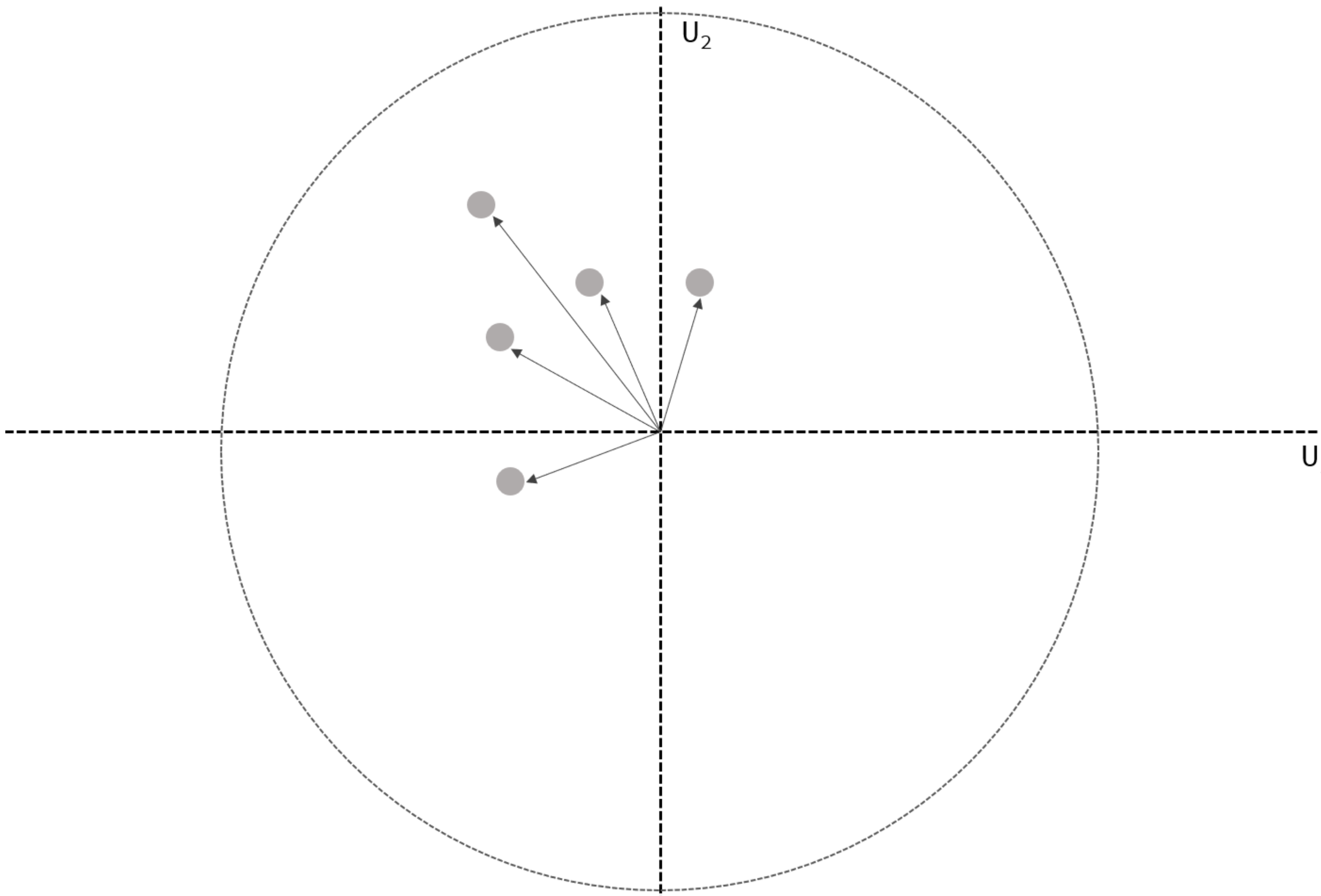
Visualizing Multiplicative Effects



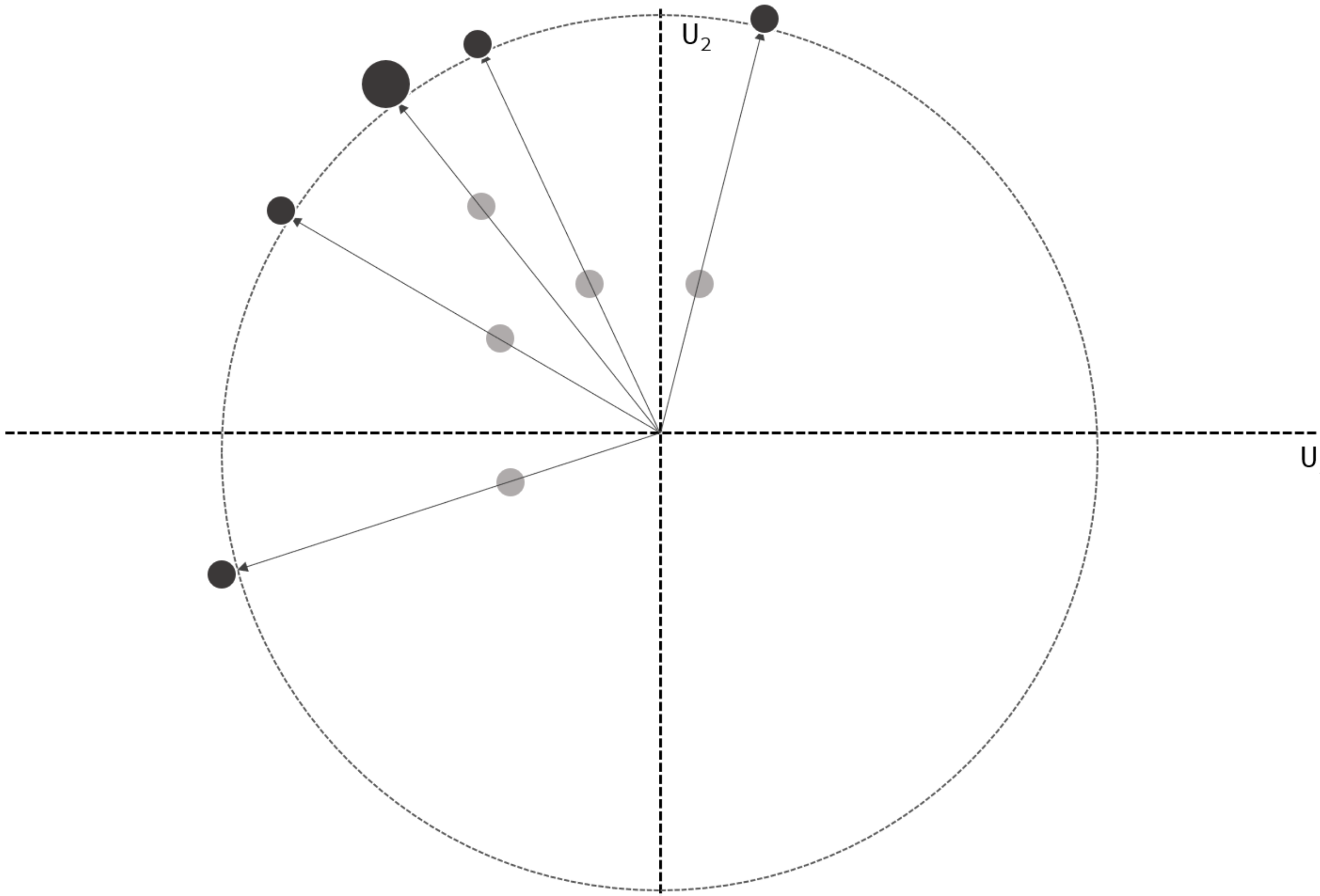
Visualizing Multiplicative Effects



Visualizing Multiplicative Effects



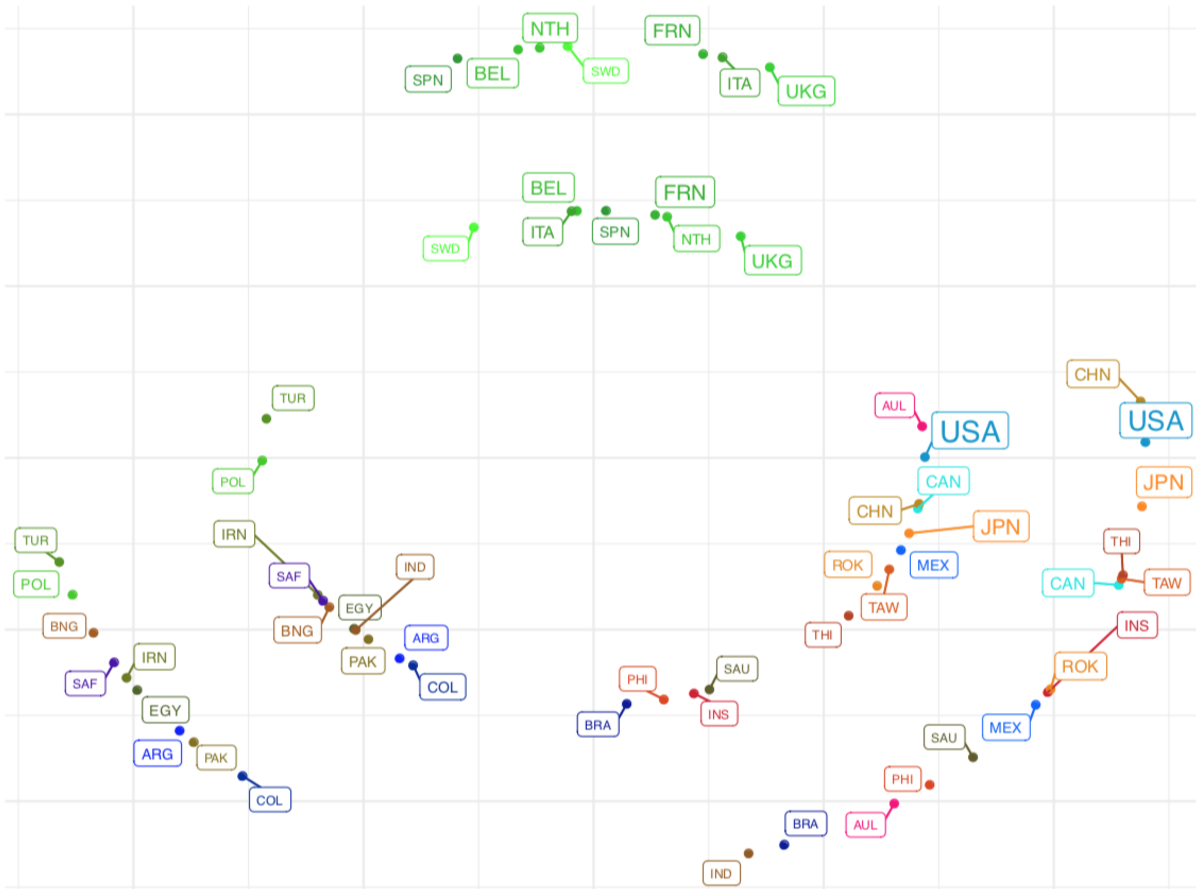
Visualizing Multiplicative Effects



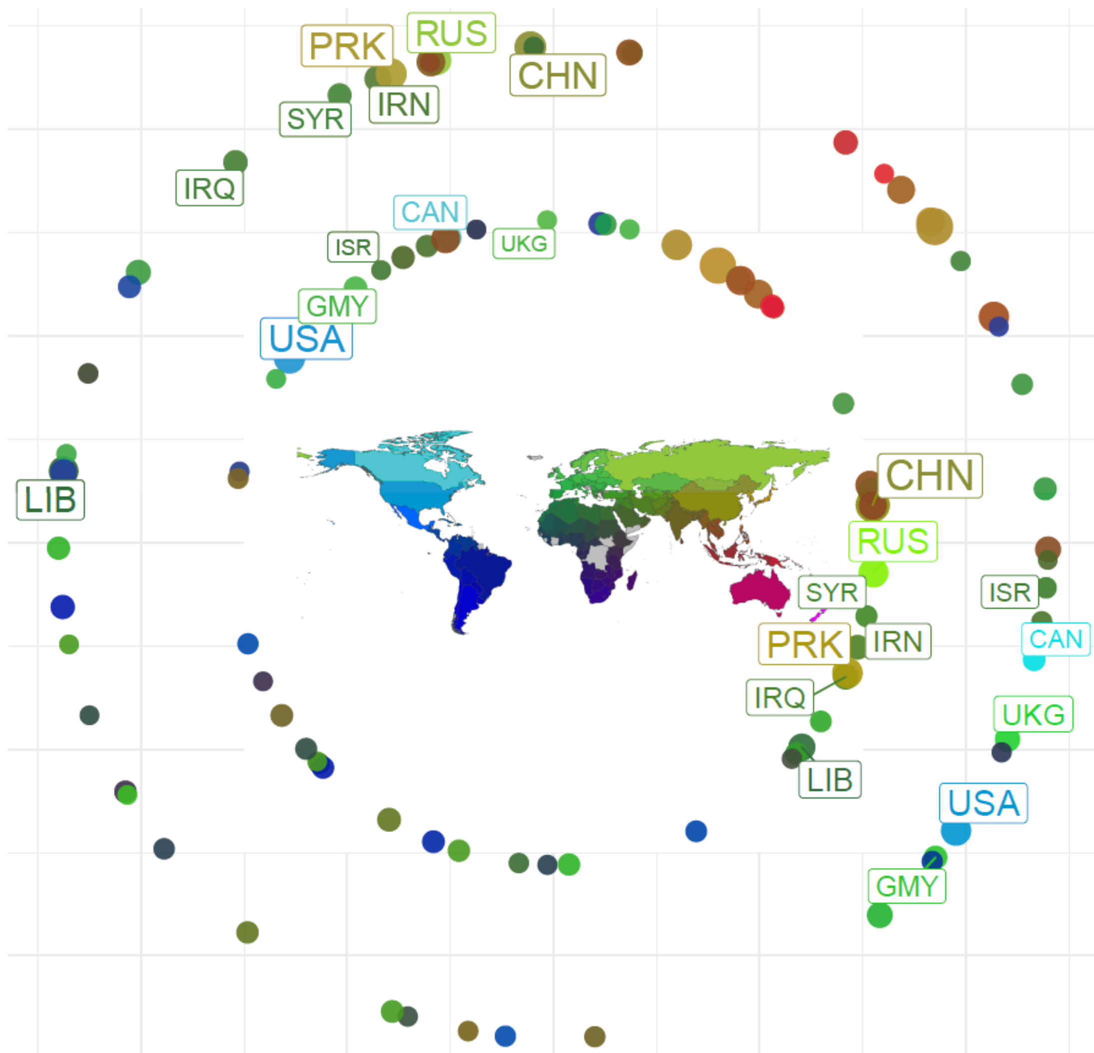
Visualizing the multiplicative effects

```
load('tradeMapCols.rda')
x=ggCirc(
  Y=Y, U=fitAME$U, V=fitAME$V,
  vscale=.6, prange=c(2,5),
  lcol='gray85', ltype='dotted', lsize=.5,
  force=2, maxIter = 3e3,
  showActLinks=FALSE, geomLabel=TRUE, geomText=FALSE,
  geomPoint=TRUE,color=names(rep(ccols,2))
  ) +
  scale_color_manual(values=rep(ccols,2)) +
  theme_bw() +
  theme(
    legend.position='none',
    axis.ticks=element_blank(),
    axis.text=element_blank(),
    panel.border=element_blank(),
    axis.title=element_blank()
  )
```

Visualizing the multiplicative effects



Example from different context



Benefits of this approach

- At its core, AME is just a GLM with random effects used to ensure that we can treat dyadic observations as conditionally independent
- AME can be used:
  - on both undirected and directed data,
  - on longitudinal and static networks,
  - and on a variety of distribution types we commonly encounter in political science (binomial, gaussian, and ordinal).

Summary

- LFM is a powerful framework that has proven useful
- A lot of other things going on:
    - Community structure in longitudinal, multidimensional arrays (Mucha et al. 2010)
    - Multilinear tensor regression (Hoff 2015, Schein et al. 2015, Minhas et al. 2016)
    - Intersection of network based methods to text analysis (Henry et al. 2016, Huang et al. 2015)
- Takeaway here is that these methods are useful when we study systems in which interactions are interdependent
- These interdependent relations may at times be of interest themselves or in other cases may just help us to better predict

Taking Dyads Seriously: Simulation

- Through a simulation study, we highlight the utility of AME as an inferential tool for dyadic analysis.
- Most scholars working with dyadic data are primarily concerned with understanding the effect of a particular independent variable on a dyadic dependent variable.
- The goal of our simulation is to assess how well AME can provide unbiased and well-calibrated estimates of coefficient parameters in the presence of unobserved dependencies.

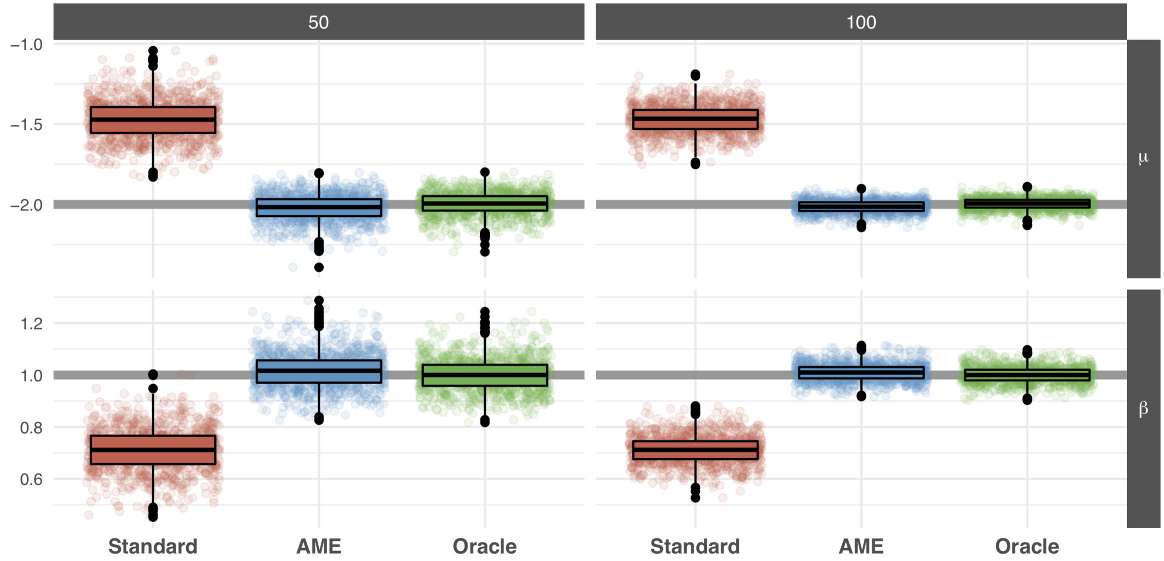
Assume that the true data-generating process for a particular Y is given by:

$$y_{i,j} \sim \mu + \beta x_{i,j} + \gamma w_{i,j} + \epsilon_{i,j}$$

- Y can be thought of as a dyadic dependent variable, X and W are both dyadic covariates that are a part of the DGP for Y, but W is not observed. We compare inference for μ and β. β would be the main focus for applied scholars

Taking Dyads Seriously: Simulation

Regression parameter estimates for the standard, AME, and oracle models from 1,000 simulations. Summary statistics are presented through a traditional box plot, and the estimates from each simulation are visualized as well as points.

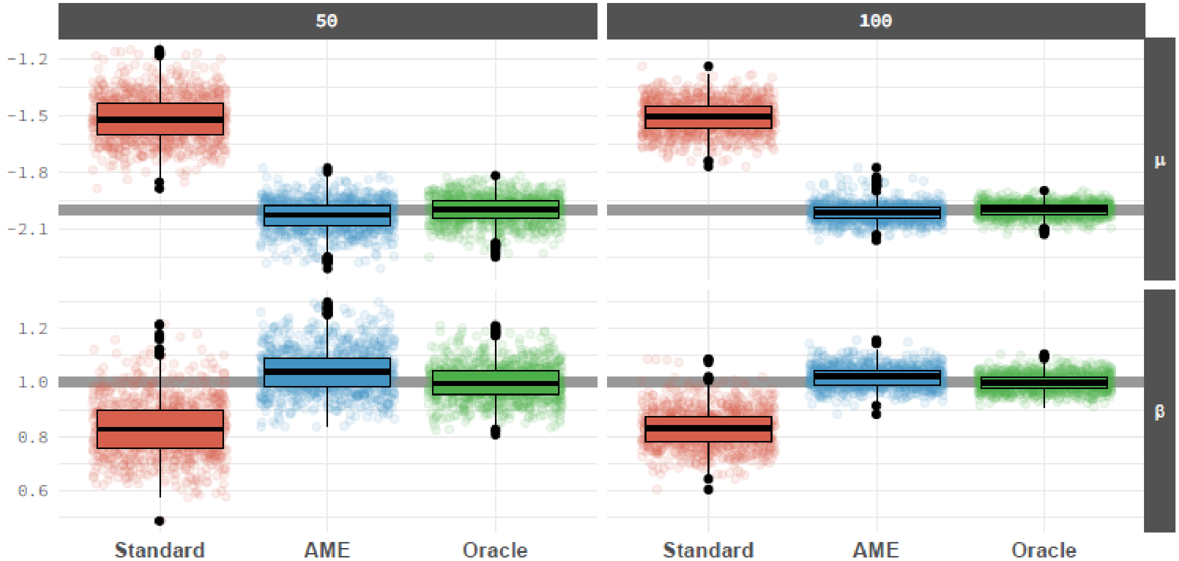


Taking Dyads Seriously: Simulation

Proportion of times the true value fell within the estimated 95% confidence interval for the standard, AME, and oracle models from 1,000 simulations.

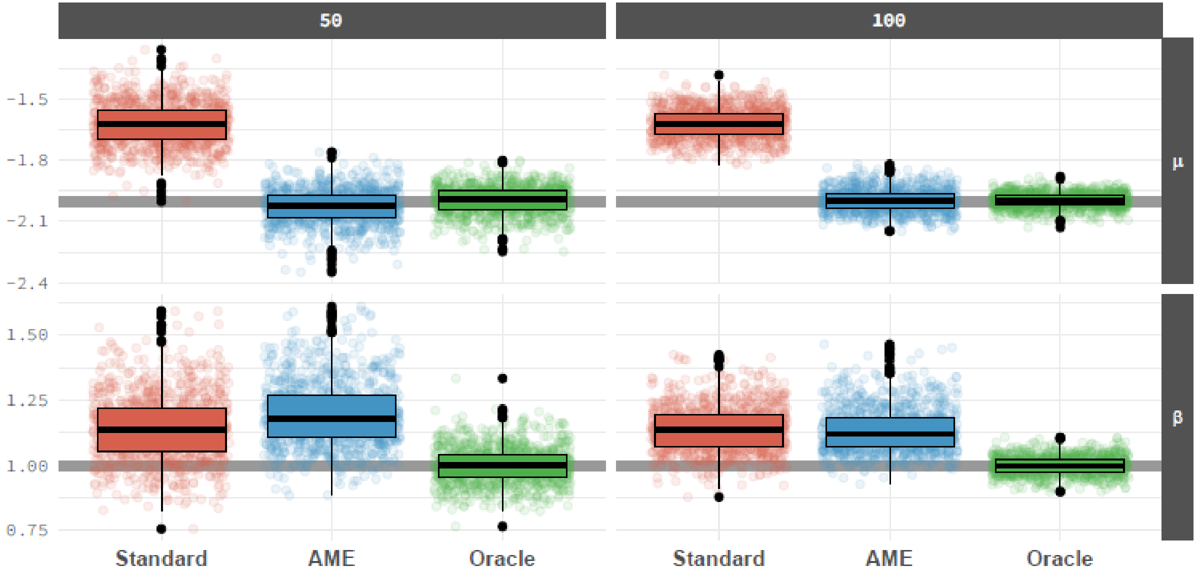
There is a but

Estimation is more challenging when the omitted variable is correlated with the observed variable. X and W are correlated at 0.4 in this case.



There is a but

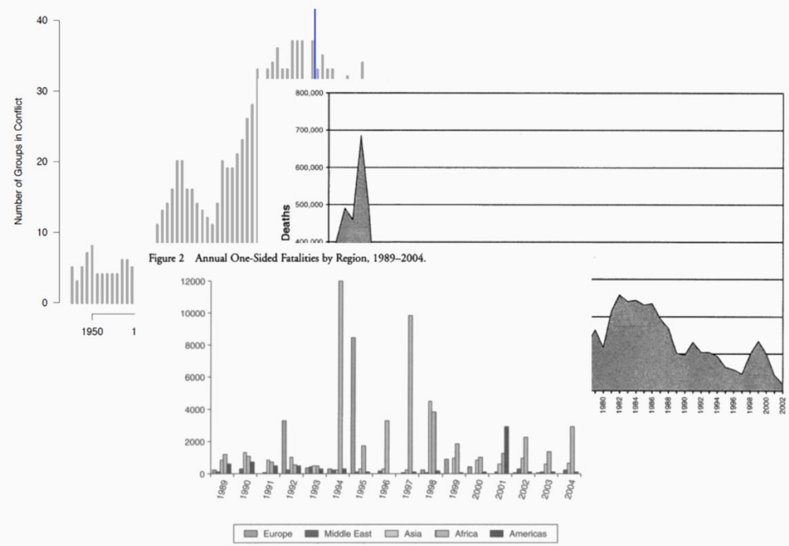
Estimation is more challenging when the omitted variable is correlated with the observed variable. X and W are correlated at 0.7 in this case.



Application to Studying Intrastate Conflict in Nigeria

Motivation: extensive literature predicting violence between actors and trying to understand why battles occur.

Hegre et al. (2001)
Fearon & Laitin (2003)
Collier et al. (2004)
Salehyan (2013)
K.G. Cunningham (2013)
Sambanis & Shayo (2013)
Lacina (2014)
Prorok (2016)



Roughly a third of all intrastate conflict between 1989 and 2003 have been fought with multiple warring parties (UCDP/PRIO 2007).

Networks of Violence: Motivation

> "Existence of multiple rebel groups means we can no longer understand civil wars with a sole focus on state attributes. In fact, the government's strategies leading to victory, defeat, or continuation of war can only be understood in relation to the rebel group/groups it is fighting." Akcinaroglu (2012)

Networks of Violence: Motivation

Motivation: we argue

(1) this is a network question, and should be answered as such and

(2) previous patterns of interdependence will actually help us explain conflict better

Our Paper:

1. Intrastate conflicts are a complex system composed of multiple actors in conflict
2. Armed actors & battles = nodes and ties in a network
3. Novel model captures relationships endogenous to the conflict system
4. Our approach provides precise estimates & out performs standard approaches
5. Uncovers important relational patterns of conflict with substantive implications for the study of conflict processes

Networks of Violence: Motivation

Missing information in previous work: How does evolution in the structure of relationships influence conflict over time?

- 1st-order: Sender effects
- 2nd-order: Reciprocity
- 3rd-order: Homophily & Stochastic equivalence
- System level: Changing actor composition

In the paper, and in our usual presention then we walk through the meaning of each of these effects, just like we have for you.

Here we tie them to empirical examples from the conflict literature.

Networks of Violence: Dependencies

First-order effects

- In the civil conict network, some actors are more likely to fight than others due to their group-level characteristics.
- For example, Weinstein (2007) argues that rebel groups with more ideologically motivated followers are thought to be less violent than groups whose members are motivated by greed.
- The motivation of group members, then, is a latent, unobserved attribute that accounts for why one rebel group is more prone to attack other groups.
- Another example of first order dependence is when a contextual feature of the group makes it more likely to be a target.
- For instance, if a group possesses territory with valuable natural resources, they are more likely to be attacked by groups that are more motivated by resources.

Networks of Violence: Dependencies

Second-order effects

- Networks of civil confict are not created only by the attributes of armed groups, they are also a consequence of armed groups' actions.
- Condra & Shapiro (2010) and Lyall (2009) have explored how armed groups affect the tendency of their targets to be violent
- In the future, and many scholars have examined how rebel groups respond to violence with violence some violence is simply retaliatory in nature!

Networks of Violence: Dependencies

Third-order effects

Homophily/Heterophily

- ideological motivations (similar targets)
- material resource motivations (geography determines targets)

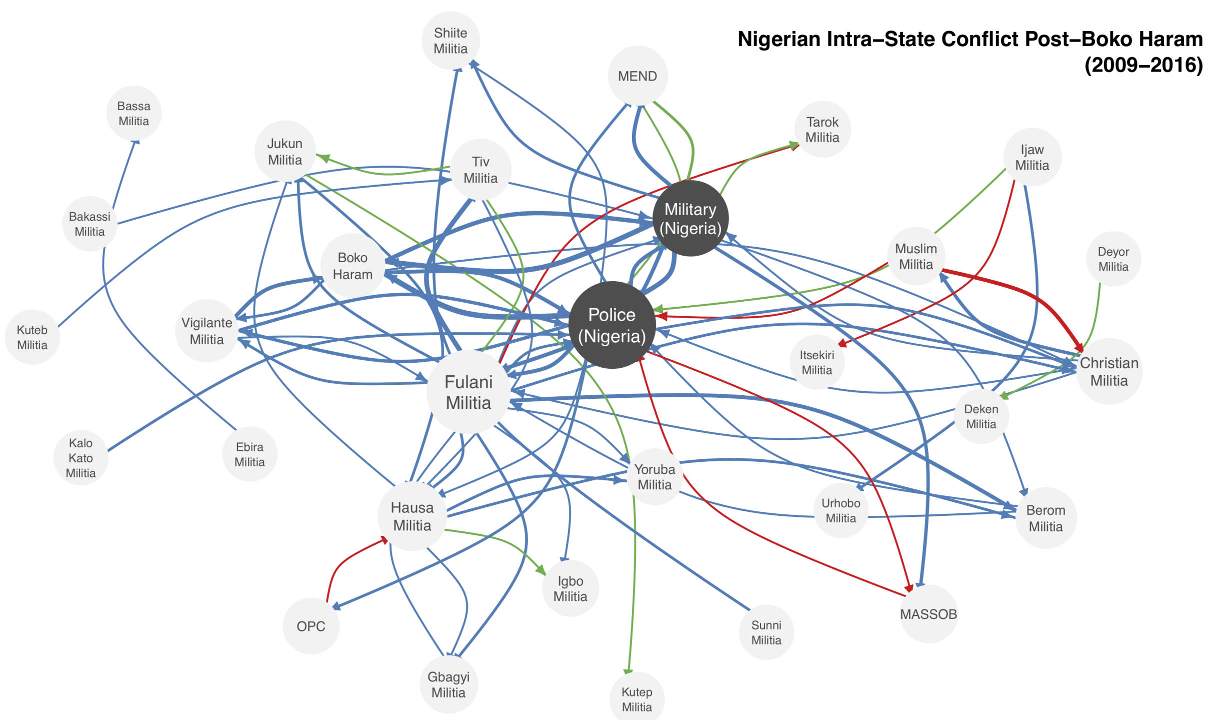
Stochastic Equivalence

- Same foreign sponsor (Bapat and Bond, 2012)
- Alliances (Zeigler, 2016)

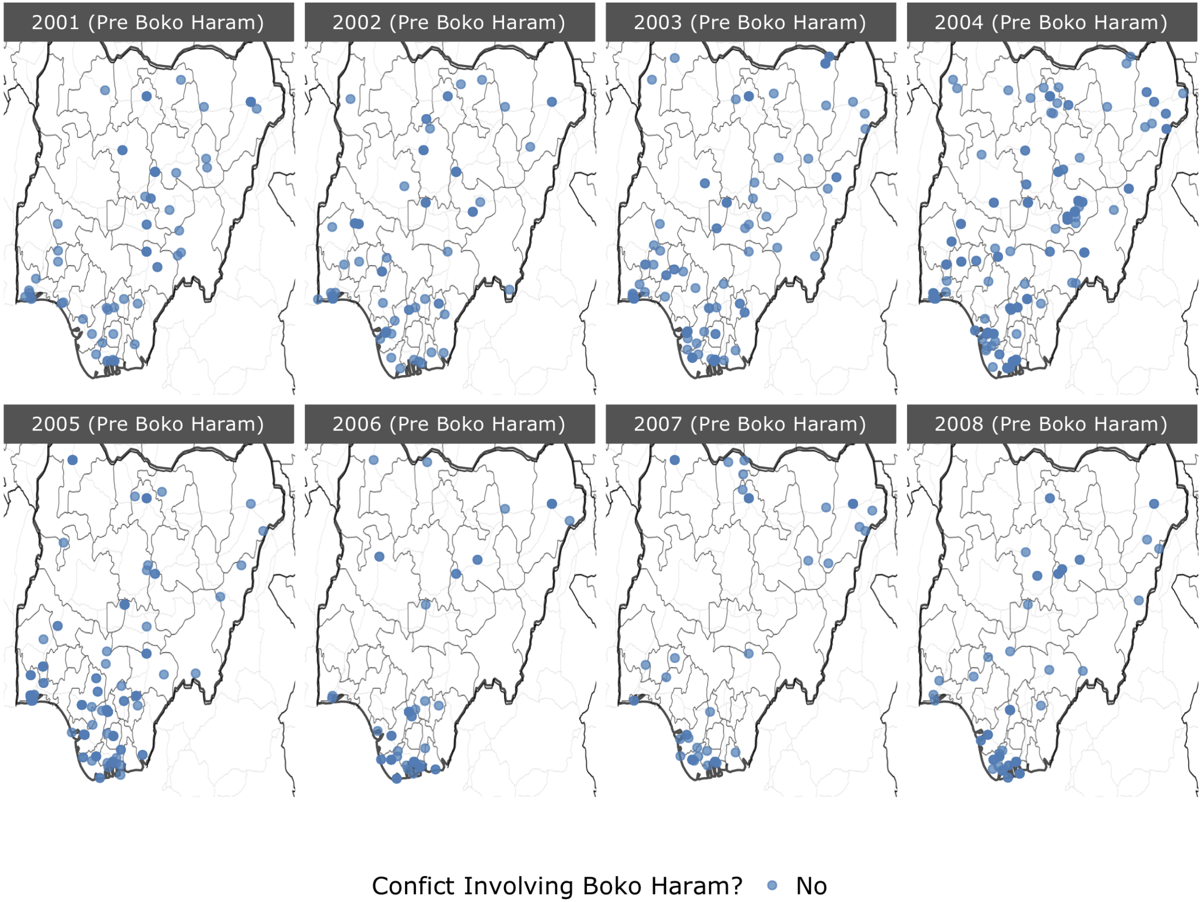
Networks of Violence: Nigeria

After lying this ground work, we then defend our model and next we move into explaining (and defending) the case. Nigeria: illustrating the network

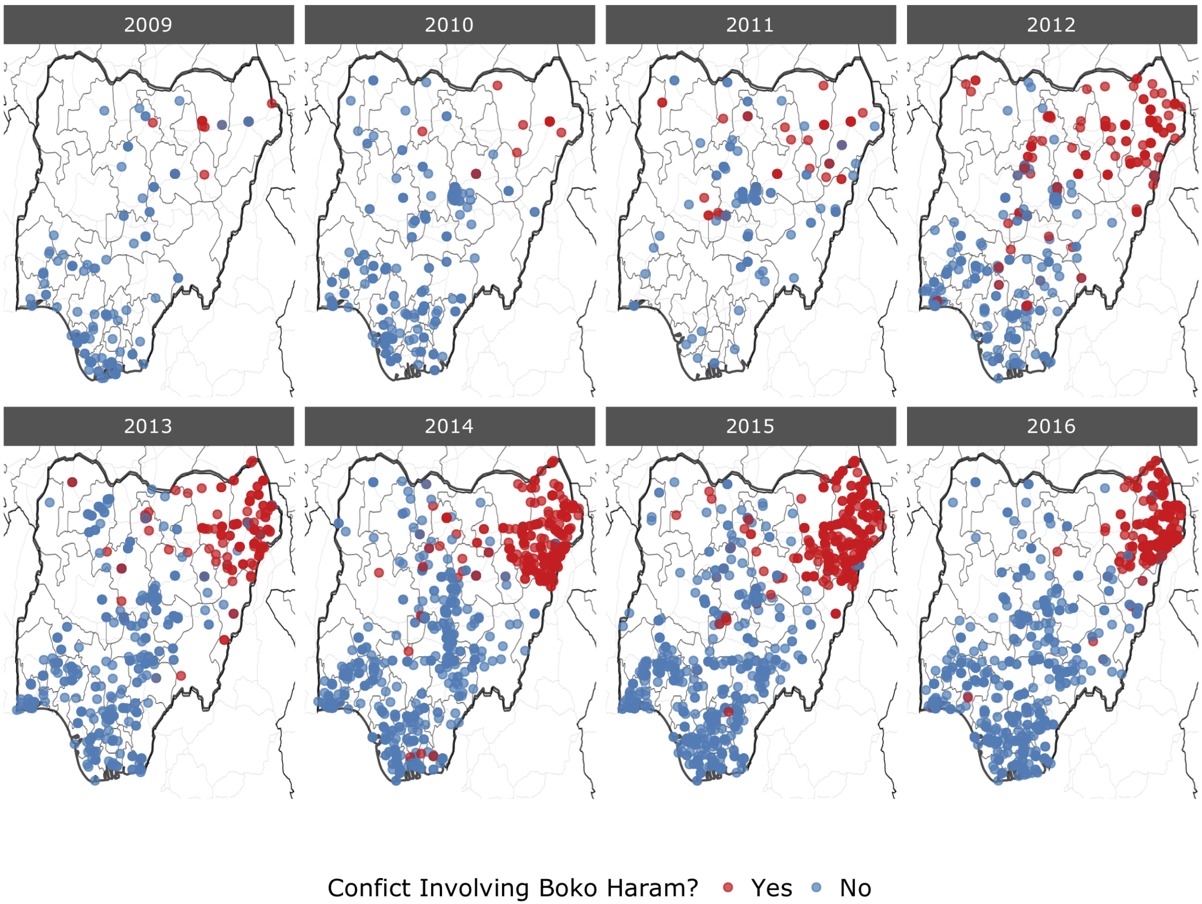
- Multi-actor conflict
- Intensity of violence changes over time
- Relationships between actors change over time



Networks of Violence: Nigeria



Networks of Violence: Nigeria



Networks of Violence: Data

Armed Conflict Location and Event Data Project (ACLED) developed by Raleigh et al. (2010)

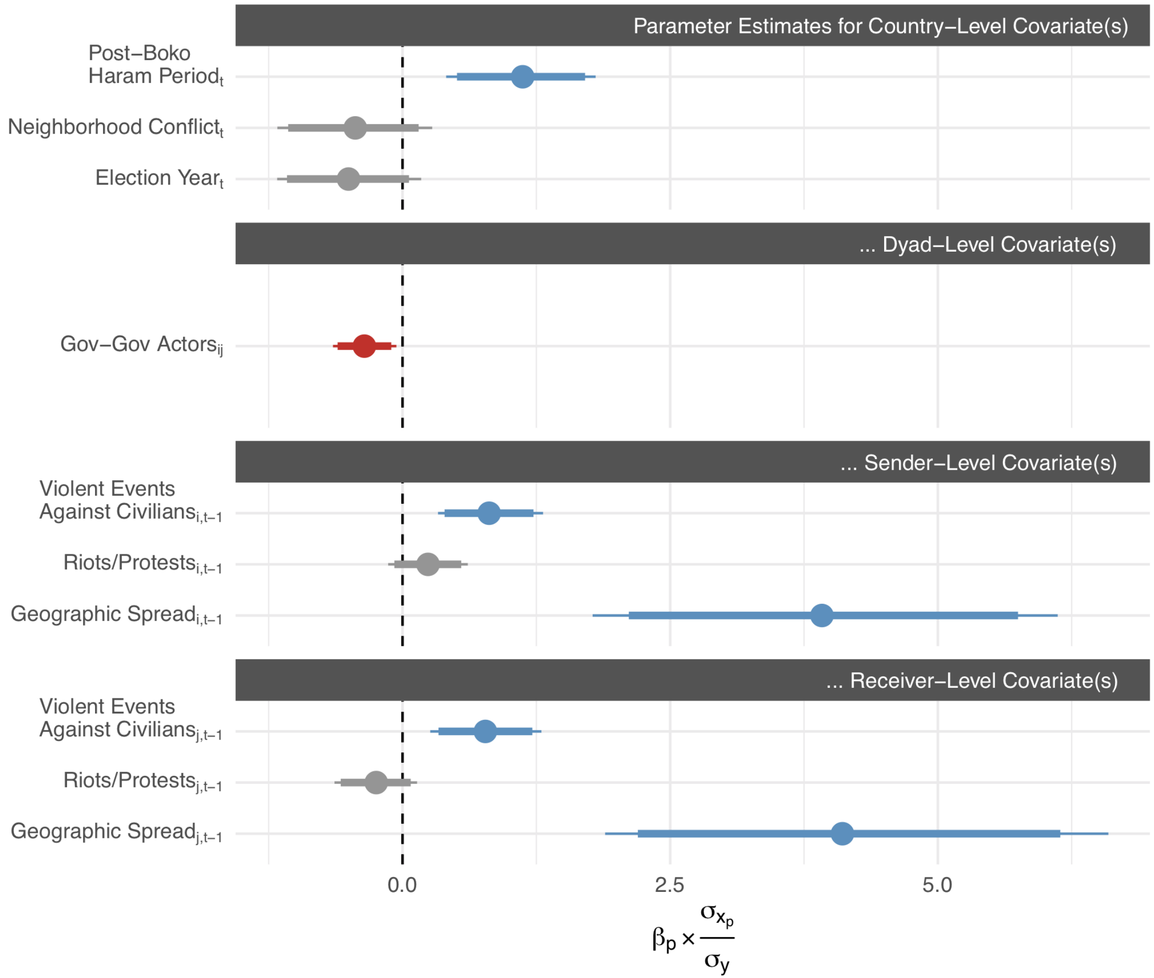
- ACLED records armed conflict and protest events in over 60 developing countries
- We use ACLED battles data for Nigeria to generate a measure of conflict where:
- $y_{ij,t}$ = 1 indicates that a conflict occurred when actor i attacked actor j at time t
- $y_{ij,t}$ = 0 if no conflict occurred
- We focus only on modeling the interactions between armed groups that are engaged in battles for at least 5 years during the 2000-2016 period, which results in a total of 37 armed groups

Networks of Violence: Measurement

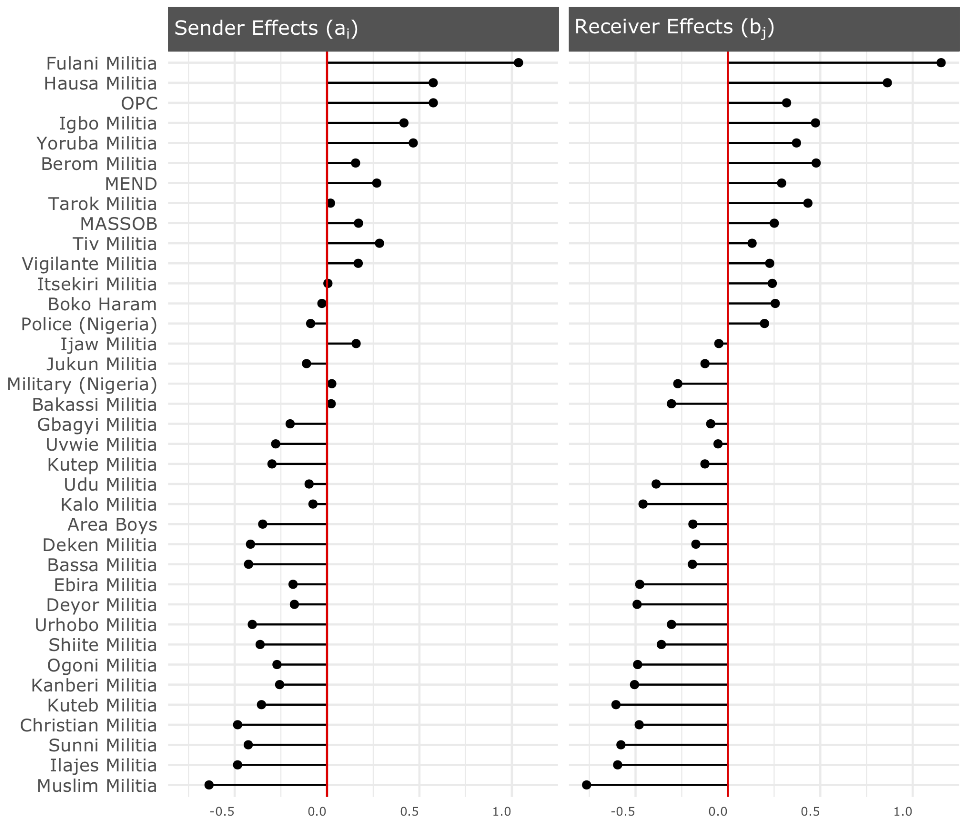
Model covariates

- $y_{ij;t}$ = whether or not conflict occurs.
- changing actor composition: we adjust the estimation procedure of the AME model so that actor observations only contribute to the likelihood of the model once they enter into the network
- civilian action: count of the number of protests/riots led by civilians against a given actor at time $t-1$
- civilian victimization: a count of the number of violent actions that an actor committed against civilians at time $t-1$
- geographic spread (sender and reciever): how dispersed a rebel group's activity is across the country
- control for government actor
- control for election year
- indicator for BK's entry

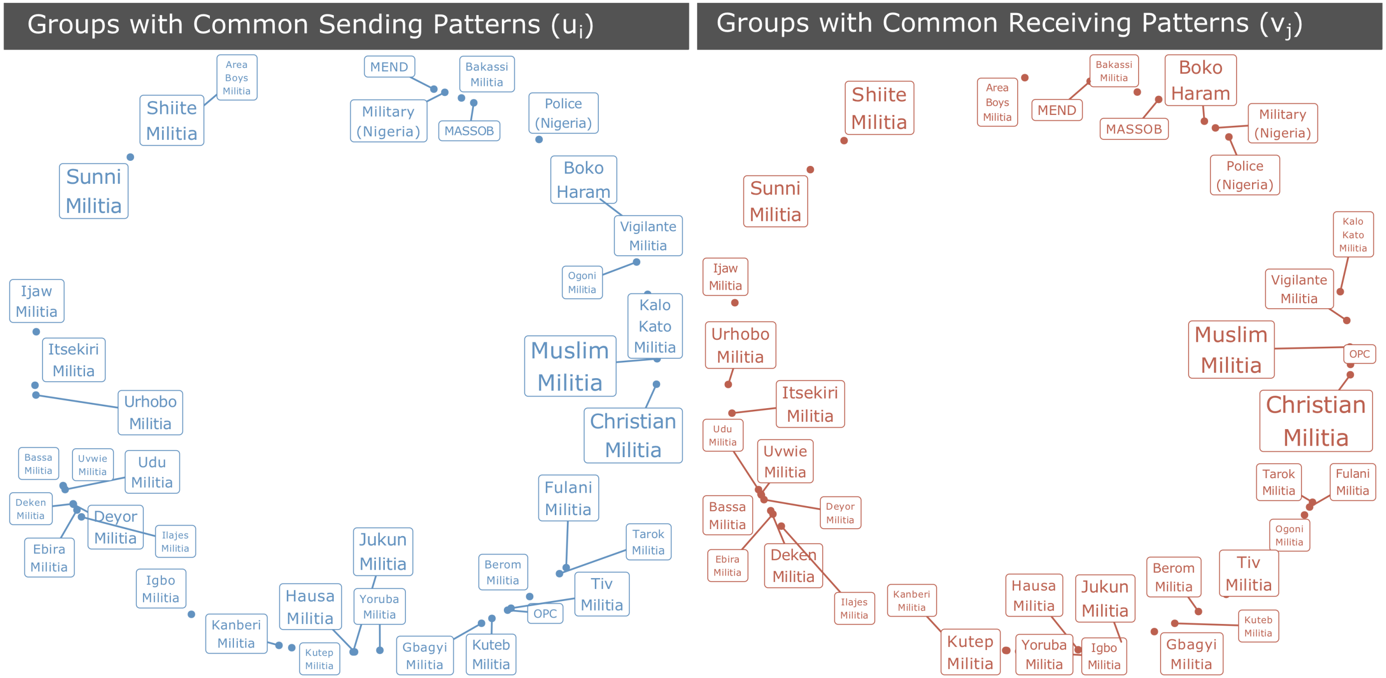
Networks of Violence: Results



Networks of Violence: Results

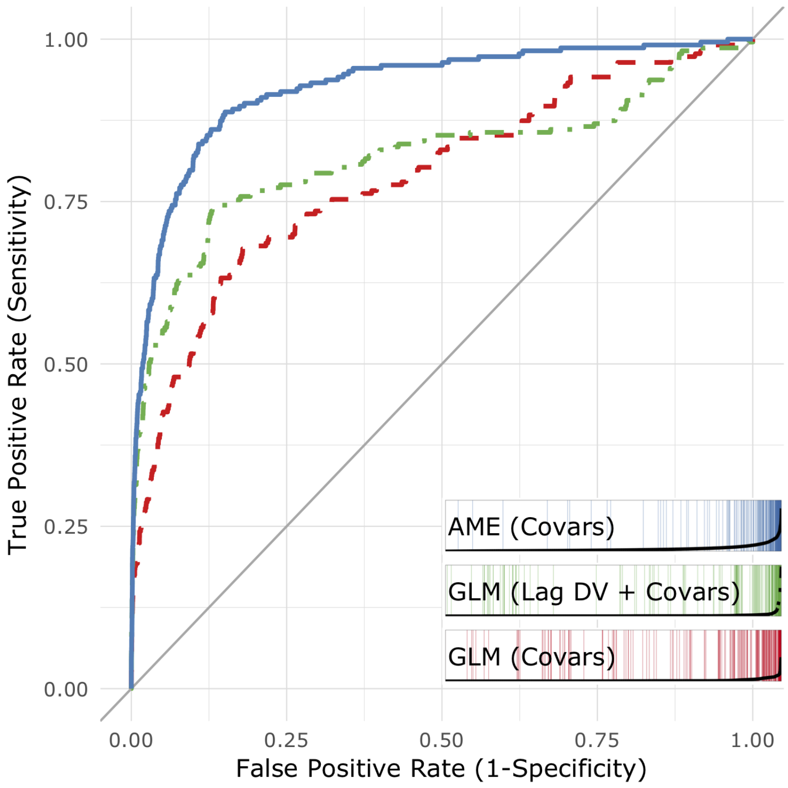


Networks of Violence: Multiplicative effects



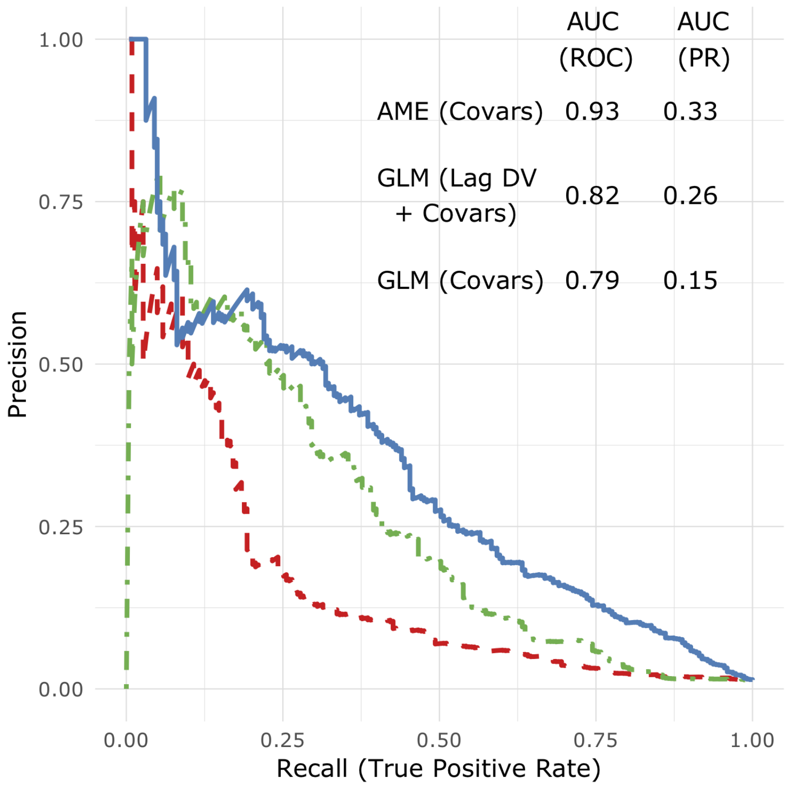
Networks of Violence

Out of sample cross-validation : ROC



Networks of Violence

Out of sample forecast: PR Curve



Networks of Violence

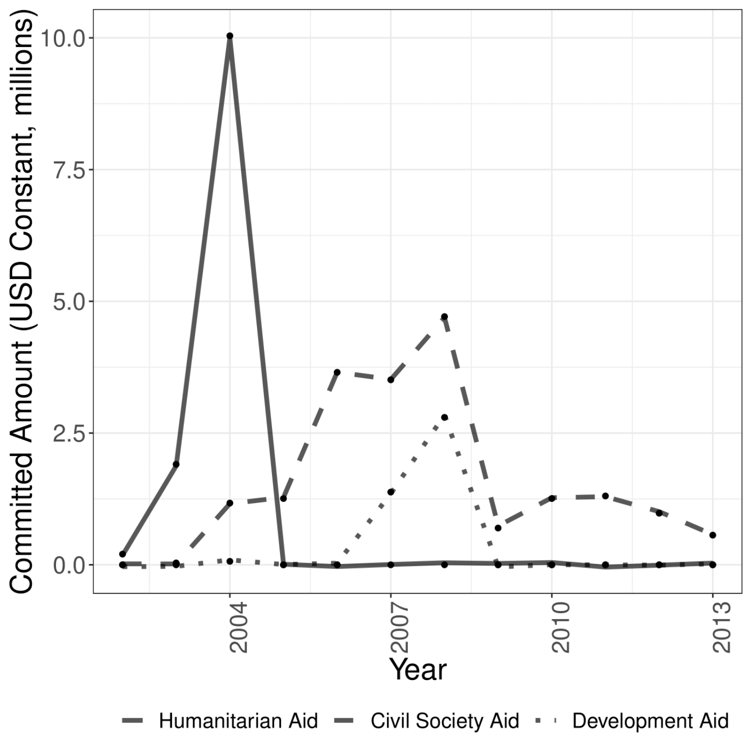
Key take-aways:

1. interdependence helps us better understand conflict in terms of why and when it occurs
2. Boko Haram's entrance does not simply increase conflict directly, it also is associated with a marked rise in violence in the dyads that do not include Boko Haram.
3. actors who target civilians are more likely to send and receive conflict themselves.

All code for this project available at: github.com/s7minhas/conflictEvolution

Keeping Friends Close

How do we explain foreign aid dispersements in the wake of natural disasters given the existing literature which finds that aid is given for strategic purposes?



Keeping Friends Close: Hyps

- H1C: Donors see natural disasters as a strategic opportunity to improve their relations with strategic opponents and are thus are likely to send more humanitarian aid to strategic opponents versus allies.

- H2: Natural disasters present an opportune window for donors to exert influence over recipients who are their strategic opponents and as such, donors are more likely to send additional \textbf{civil society aid} to their strategic opponents.

Keepings Friends Close: Modeling Strategic Interest

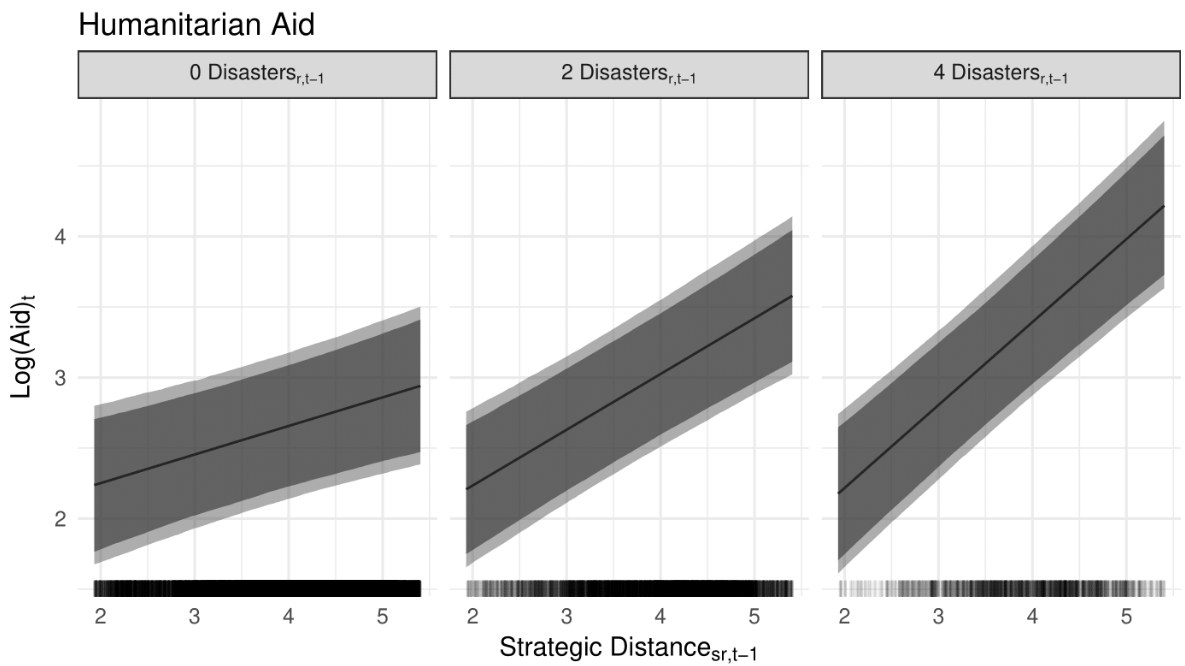
- Within this literature strategic interest takes on a variety of operationalizations, most commonly:
  - Alliances (e..g, Schraeder et al. 1998)
  - UN Voting Scores (e.g., Dreher and Fuchs 2015)
  - Common IGO Membership (e.g., Bermeo 2008)

Knowing something about the relationship between i and j as well as between i and k may reveal something about the relationship between i and k

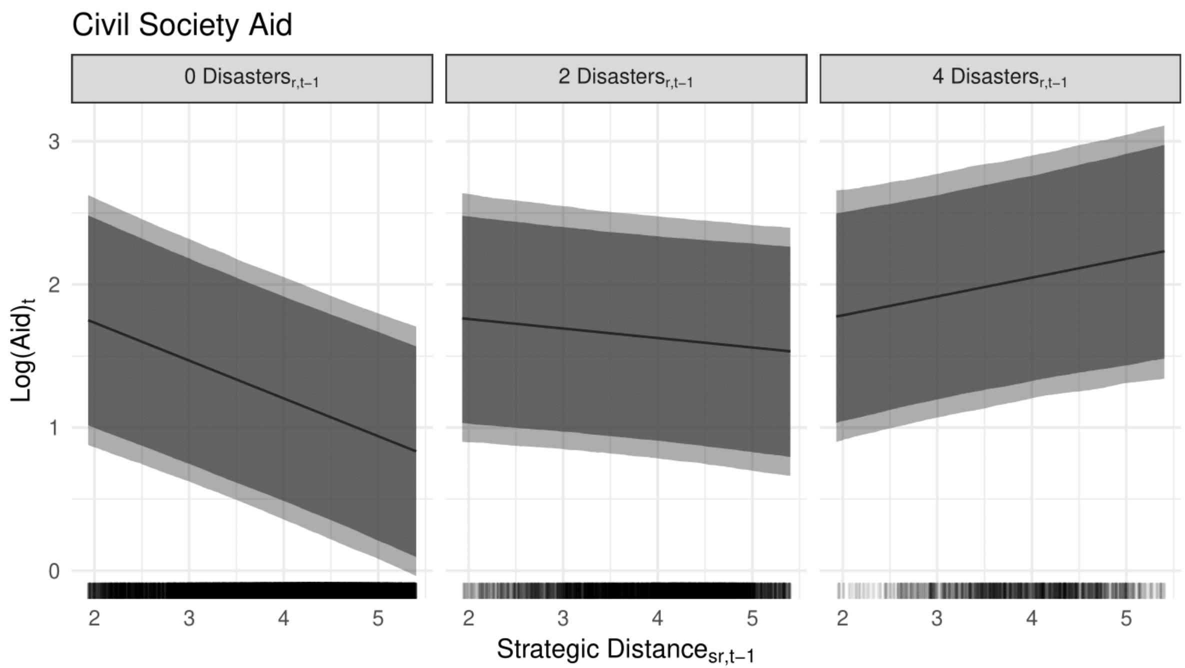
Keepings Friends Close: Downstream model

$$
\begin{aligned}
Log(Aid)_{sr,t} = {} & \beta_1(Strat.\ Distance_{sr,t-1}) \\
& +\ \beta_2(No.\ Disasters_{r,t-1}) \\
& +\ \beta_3(Colony_{sr,t-1})\ +\ \beta_4(Polity_{r,t-1}) \\
& +\ \beta_5 Log(GDP\ per\ capita_{r,t-1})\ +\ \beta_6(Life\ Expect_{r,t-1}) \\
& +\ \beta_7(Civil\ War_{r,t-1}) \\
& +\ \beta_8(Strat.\ Distance_{sr,t-1} \times No.\ Disasters_{r,t-1})
\end{aligned}
$$

Keepings Friends Close: Results



Keepings Friends Close: Results



Code available at: github.com/s7minhas/foreignAid

[W]hat lies beneath: Origins

Project started through a conversation with a non-profit interested in monitoring violent conflict and civilian victimization

- Them: We want you to predict sub-national conflict in South Sudan
- Me: Sure that's possible!
- Them: And we want predictions at the state level in South Sudan
- Me: Hmmm, well do you have data other than conflict at the state level?
- Them: Hahah
- Them: Also yearly and monthly level predictions are useless to us, we want to know what's going to happen at the weekly level AND we want to know every week
- Me: Ummm … lets just agree to pretend we never met

[W]hat lies beneath: Origins

- Them: We'll pay you
- Me: Lets do this.

[W]hat lies beneath: Features?

- Of course we can start with a lagged DV model to get all the zeros and persistent conflicts
- But how to get at new onsets for the state-week level in a country like South Sudan …
- Modeling diffusion: spatial lag framework ($y{*t*} |*sim* |*rho W y*{t-1}$)
- Incorporating spatial lags of conflict with W matrices based on distance helped!
- But … multiple conditions beyond geography can drive the spread of violence, such as refugee flows, ethnic group locations, etc.
- Getting data for these various features in real time at the weekly level is difficult

[W]hat lies beneath: Give the money back?

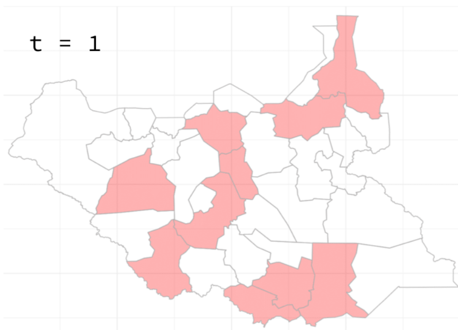
Never!

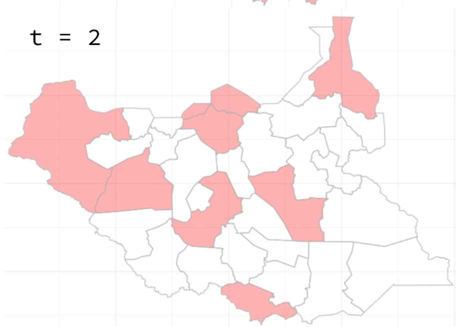
- Well … what we are doing when we incorporate geographic based spatial lags is accounting for a possible dependence between units

- We can use a network approach to estimate a latent connectivity matrix that can represent a variety of possible diffusion patterns

[W]hat lies beneath: Feature Generation Pipeline

South Sudan Spatial Conflict Data





Rule to Convert from
Spatial to Network-Like Structure

	Akobo	...	Nile
Akobo	NA	...	$y_{A,N,t}$
$\vdots$		$\ddots$	
Nile	$y_{N,A,t}$	...	NA

where:

$$y_{A,N,t} = 1 \text{ iff } y_{A,t-1} = 1 \ \& \ y_{N,t-1} = 0, \text{ and}$$
$$y_{N,A,t} = 1 \text{ iff } y_{N,t-1} = 1 \ \& \ y_{A,t-1} = 0$$

Determine Likely Diffusion
Paths Between Provinces
Accounting for Network
Dynamics

$$y_{ij} = f(\theta_{ij}), \text{ where}$$
$$\theta_{ij} = \mathbf{u}_i^\top \mathbf{D} \mathbf{v}_j$$

Save predicted
probabilities from
the model

	Akobo	...	Nile
Akobo	NA	...	$\hat{y}_{A,N,t}$
$\vdots$		$\ddots$	
Nile	$\hat{y}_{N,A,t}$	...	NA