How small wars become big(er) wars: latent dynamics of conflict and the role of peacekeeping

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FOCUS DRIVEN STATISTICAL INFERENCE WITH COMPLEX DATA

Gudmund Horn Hermansen[1,2]
Håvard Mokleiv Nygård[3]

[1] Department of Economics, Norwegian Business School
[2] Department of Mathematics, University of Oslo
[3] Peace Research Institute Oslo

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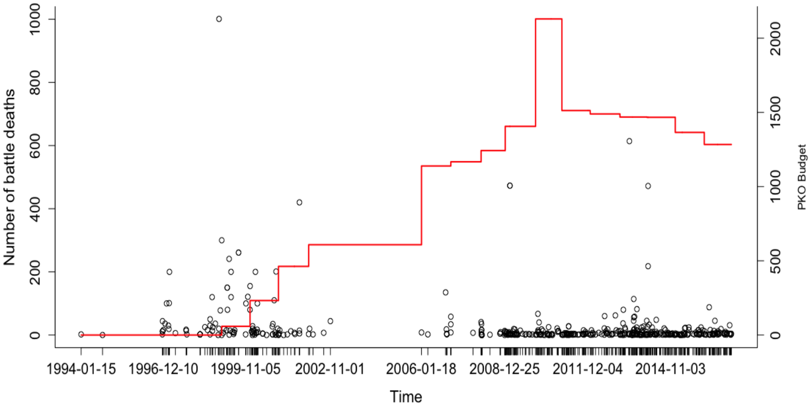
Introduction and summary

Preliminary models, ideas and some results for some statistical models for the intensity and escalation in wars and violent conflicts.



What is intensity and what is escalation?

The plan

1) Current state on conflict (and escalation) research
2) Why a latent model?
3) A class of statistical model for intensity and escalation in war and violent conflicts
4) Properties, simulations and simple illustrations
5) A dynamic data-dependent prior framework
6) Illustration with covariates (PKO)

The current understanding of war and conflict escalation

Conflict research has spent the last 20 years doing systematic, largely statistical, studies to understand:

- why civil wars break out
- how they are sustained and
- when and how durable post-conflict peace is possible

Much less energy has been spent understanding the dynamics of conflict, i.e. the underlying intensity and escalation process(es).

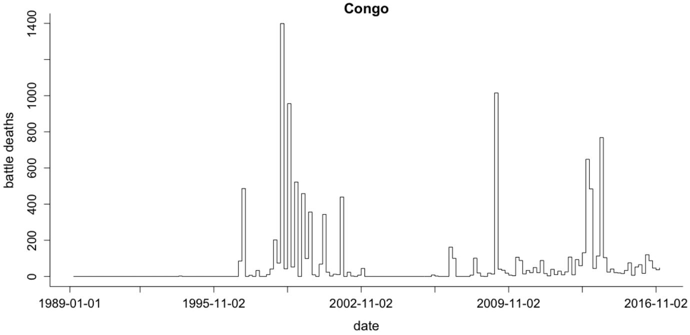
The main goals are to understand why and when

- non-violent conflicts become violent
- when low intensity conflict becomes high intensity

The state-of-the-art aim at modelling the differences between smaller and bigger wars, typically relying on off-the-shelf tools (e.g. markov models).

We also intend to investigate and build (new) statistical models with focus on good representation of the underlying intensity and escalation process.

Why a latent model?



Let y_t be the number of battle deaths and consider the general (toy) model

$$y_t \mid \theta_t \sim f(y_t \mid \theta_t)$$
$$\theta_t \mid y_{t-1}, \phi \sim \pi(\theta_t \mid y_{t-1}, \phi),$$

with θ_t as a latent process that depend on the previous observation y_{t-1}.

We will think of the latent θ_t as the intensity, which can be modelled as:

- states (e.g. hidden markov model)
- smooth functions or
- stochastic

A Poisson-Gamma model for the intensity

Let y_t be the number of battle deaths at time t and consider the model

$$y_t \mid \theta_t \sim \text{Poisson}(\theta_t)$$
$$\theta_t \mid y_{t-1}, a, b, c \sim \text{Gamma}(c(a + by_{t-1}), c)$$

where $a > 0$, $c > 0$ and $0 < b < 1$.

We need $|b| < 1$ to ensure that y_t has a finite expectation as $t \to \infty$.

For this model, we may view

- a as baseline intensity
- b as a type of escalation parameter and
- c as the rate/chance of battle death(s) (i.e. $y_t > 0$)

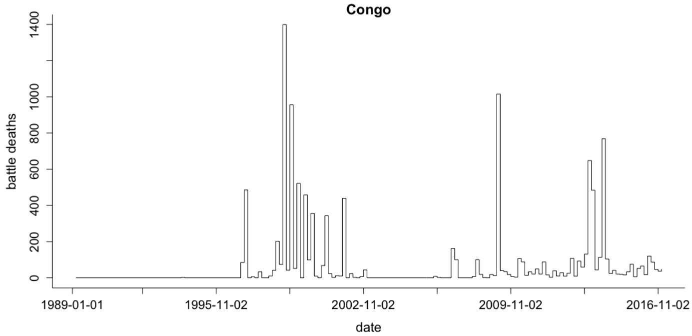
Why not

$$\theta_t \mid \theta_{t-1}, a, b, c \sim \text{Gamma}(c(a + b\theta_{t-1}), c)$$

or

$$\theta_t \mid y_{t-1}, a, b, c \sim \text{Gamma}(ce^{a+by_{t-1}}, c)$$

Yes, it is an extremely simplified model



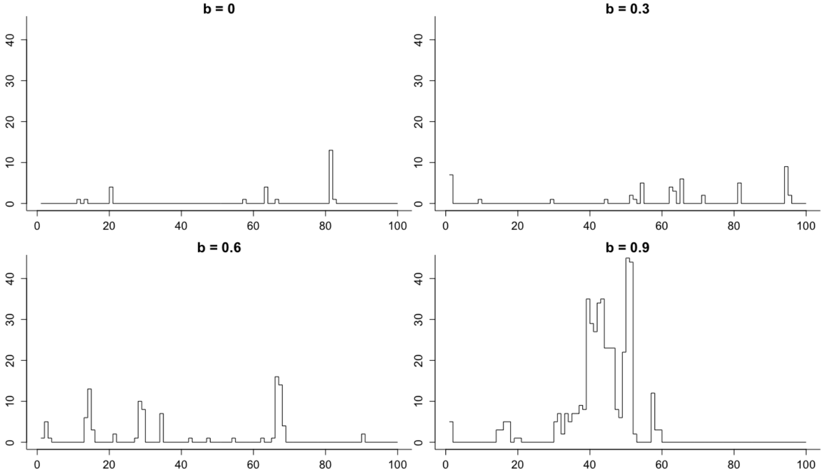
Clearly a simplification of the dynamics of real wars and violent conflicts.

It is a starting point and toy model we intend to expand by incorporating more complex (time or spatial) dynamics and covariates.

It is a simplification, the question is then whether it is sufficiently complex to enable relevant inference.

Simulations from the Poisson-Gamma model

Simulated 100 time steps from the from the Poisson-Gamma model with $a = 0.4$, $c = 0.1$ and $b = (0.0, 0.3, 0.6, 0.9)$.



A negative binomial model for escalation

Furthermore, if we integrating out all the θ_t, we obtain

$$
\begin{aligned}
f(y_2, \ldots, y_n \,|\, y_1, a, b, c) &= \prod_{t=2}^{n} \frac{1}{y_t!} \frac{\Gamma(y_t + c(a + by_{t-1}))}{\Gamma(c(a + by_{t-1}))} \frac{c^{c(a+by_{t-1})}}{(c+1)^{y_t + c(a+by_{t-1})}} \\
&= \prod_{t=2}^{n} \mathrm{NB}(y_t \,|\, r_t, p),
\end{aligned}
$$

where $r_t = c(a + by_{t-1})$ and $p = 1/(c+1)$.

From this, it is clear that $y_t \,|\, y_{t-1}$ is negative binomial for $t > 1$, and from the properties of the negative binomial distribution we may think of

$$
y_t = \epsilon_t + \sum_{i=0}^{y_{t-1}} \delta_i,
$$

where ϵ_t and δ_i are independent and

$$
\epsilon_t \sim \mathrm{NB}(ca, p) \quad \text{and} \quad \delta_i \sim \mathrm{NB}(cb, p),
$$

which provides insight into the interpretation of parameters and also motivate some natural extensions.

A negative binomial model for escalation

From the above, it is clear that

$$\mathrm{E}\left[y_t \,|\, y_{t-1}\right] = a + by_{t-1} \qquad \text{and} \qquad \mathrm{Var}(y_t \,|\, y_{t-1}) = (1 + 1/c)(a + by_{t-1}),$$

which give same/more insights into the interpretation of a, b and c.

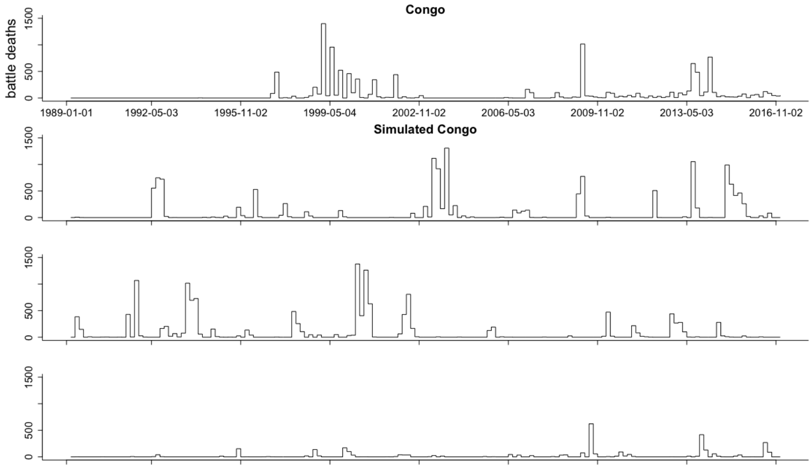
For example, with $c \to \infty$ we get the Poisson autoregressive model.

Furthermore, it follows that for $0 < k < t$ we have that

$$\mathrm{E}\left[y_t \,|\, y_{t-k}\right] = a \sum_{i=1}^{k} b^{i-1} + b^k y_{t-k},$$

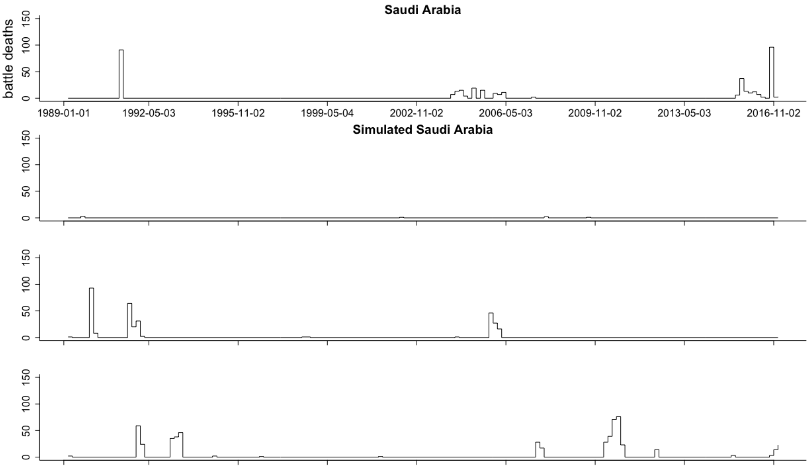
which shows that $|b| < 1$ to guarantee a finite mean; similar insights from the conditional variance.

Illustration: Estimation and simulation (Congo)



Estimated parameters for Congo $(\widehat{a}, \widehat{b}, \widehat{c}) = (25.95, 0.48, 0.0020)$.

Illustration: Estimation and simulation (Saudi Arabia)



Estimated parameters for Saudi Arabia $(\widehat{a}, \widehat{b}, \widehat{c}) = (0.68, 0.80, 0.015)$.

A dynamic and data-dependent prior formulation

Consider the following hierarchal setup

$$
\begin{aligned}
y_t \mid \theta_t &\sim f(y_t \mid \theta_t) \\
\theta_t \mid y_{t-1}, \phi &\sim \pi(\theta_t \mid y_{t-1}, \phi) \\
\phi &\sim \pi(\phi)
\end{aligned}
$$

were we think of $\pi(\theta_t \mid y_{t-1}, \phi)$ as a type of dynamic data-dependent prior, i.e. the prior for tomorrow depends on what we see today.

And if we let $f(y_t \mid \theta_t)$ be Poisson, and $\pi(\theta_t \mid y_{t-1}, \phi)$ be Gamma (with a suitable prior for ϕ) we have a similar modelling framework (as above).

Why?

- the political scientists often have priors and generally like Bayes
- the Bayesian framework may simplify certain parts related to inference

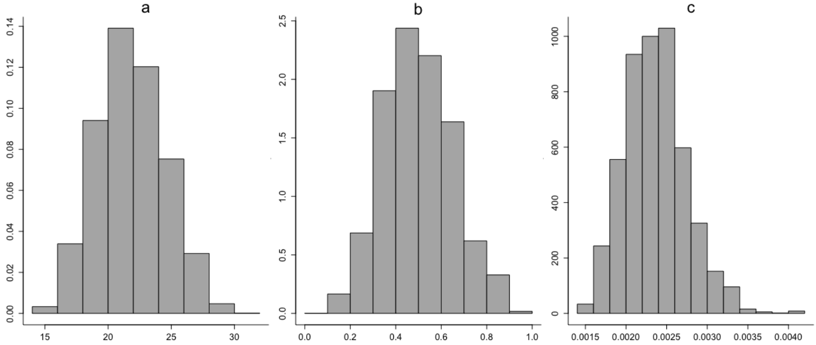
Posterior inference for Congo

To obtain a model similar to the above, let

$$y_t \mid \theta_t \sim \text{Poisson}(y_t \mid \theta_t)$$
$$\theta_t \mid y_{t-1}, a, b, c \sim \text{Gamma}(\theta_t \mid y_{t-1}, a, b, c)$$

and $a \sim \text{Gamma}(a_0, a_1)$, $b \sim \text{Uniform}(0, 1)$, $c \sim \text{Gamma}(c_0, c_1)$ we obtain via MCMC the following posteriors.

Then for Congo:



Posterior inference for Saudi Arabia

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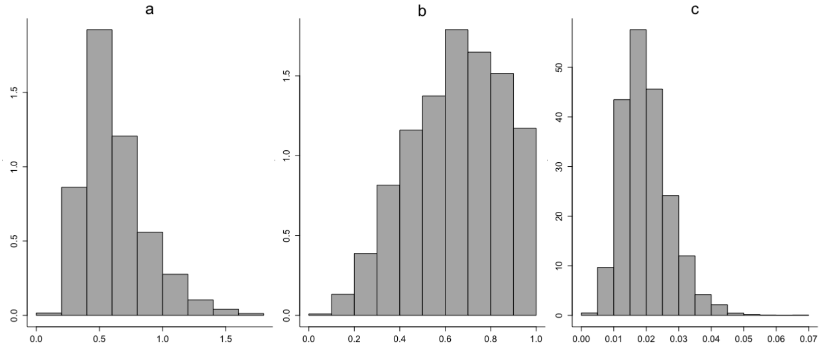

Conflict escalation and UN peacekeeping (PKO)

There are many possible choices of covariates in the political science literature.

Here, as an illustration, we consider UN peacekeeping (PKO), and the potential effect on the processes of escalation.

There are four types of PKOs mandates:

- type 1 is essentially a guy with binoculars on a hill
- type 2 is two guys with binoculars on a hill
- type 3 is armed forces
- type 4 is active and heavily armed forces

In general, there is a lack systematic understanding of how PKOs affect the conflict process.

Several potential problems, such as endogeneity, omitted variables, etc.

Illustration: Battle deaths and the effect of PKOs in Congo

Now, to include covariates, let

$$b(x_t, \beta) = \frac{1}{1 + e^{-x_t^{\mathrm{t}} \beta}}$$

with $\beta = (\beta_0, \beta_{\mathrm{PKO}})$ and $x_t = (1, x_{t,1})$ with

$$x_{t,1} = \begin{cases} 1 & \text{if PKO mandate is of type 3 or 4 in year } t \\ 0 & \text{otherwise} \end{cases}$$