Full Appendix: Who Restarts Violent Conflict? Post-conflict Government Policy and Two Types of Conflict Recurrence

November 15, 2023

Part I

Appendix

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A Conceptual and Operational Comparison with Other Schemes of Conflict Recurrence

In this section, I provide details about the difference between my conceptual framework of repeated and recast conflict with others in the literature. First of all, the minimal requirement for a conflict recurrence is that an internal armed conflict happens after a previous conflict in the same country. Though it is well understood that a civil conflict can transcend national borders and interact with international wars, most studies in conflict recurrence shares this assumption. This coding entails a problem that largely irrelevant conflicts that happen to occur in the same country may be coded as recurred conflicts (e.g. Chinese civil war and Tibet secessionism; Kashmir war and many secessionist insurgencies in the north eastern India; Biafra war and Boko Haram rebellion in Nigeria). Walter (2004) pointed out this problem and proposed that we differentiate those where "same parties" return to war and irrelevant wars. She further suggested that factors affecting civil war recurrence (she called it "repeat war") and "brand new wars" should differ.

However, her "repeat war" covers pretty much everything defined as conflict recurrence in the literature. This is because she includes general social entities such as ethnic groups as warring "parties." For example, in her coding, Burundian civil war repeated because the same parties, Tutsi and Hutu, fought again. However, the fighting organizations of Hutu varied, such as CNDD and Palipehutu-FNL. Therefore, her requirement for "repeat war" that it is fought by the same "parties" is effectively equivalent to the "same issue/stake" requirement in later studies. What I try to capture in this study is the dynamics within the same context of political conflict, such as ethnic rivalry, revolutionary movements, and secessionist movements of a specific territory, which is difficult to recognize when I focus on large societal groups themselves. In addition, civil wars that do not share any issue but happen to occur in the same country should be excluded from my analysis because the causal relevance between the previous war and the "renewed" one is at most indirect. Later, Walter (2015) redefines "repeat war" as a notion very similar to my "repeated conflict." Then, "brand new wars" and recast conflict are no longer included in her sample, rendering her later approach very similar to the partial peace approach.

Later studies confine the universe of conflict recurrence by imposing "same stakes/issues" to connect a previous war with a recurred one (Doyle and Sambanis 2006; Sambanis and Schulhofer-Wohl 2009; Kreutz 2010). This is preferred by studies who examine structural factors of conflict recurrence. However, as the conflict issue is difficult to measure and sometimes fluid, many datasets still include irrelevant cases as conflict recurrence. Zeigler (2016) examines this problem specifically about the UCDP dataset. He uses "sufficiency of linkage" in fighting groups to exclude the irrelevant cases. I adopted the same approach

to purify the sample in the Appendix E[1].

The "partial peace" approach is another popular coding rule (Nilsson 2008; Mattes and Savun 2010; Badran 2014; Walter 2015; Steinert et al. 2019). They confine the conflict recurrence as armed conflict among "peace signatories." This puts an absolute weight on the same set of armed groups to recognize conflict recurrence. This is especially popular for those who examine the bargaining relationship between the former belligerents. Their theory clearly sets (usually) two bargaining parties and their predictions only pertain to the relationship between the two. Thus, it is justifiable that they limit their sample into the bipartite relationships of warring parties. However, as I point out by citing Sambanis and Schulhofer-Wohl (2009) in the main text, this approach ignores the possibility that a certain peace settlement may aggrieve the outside actors.

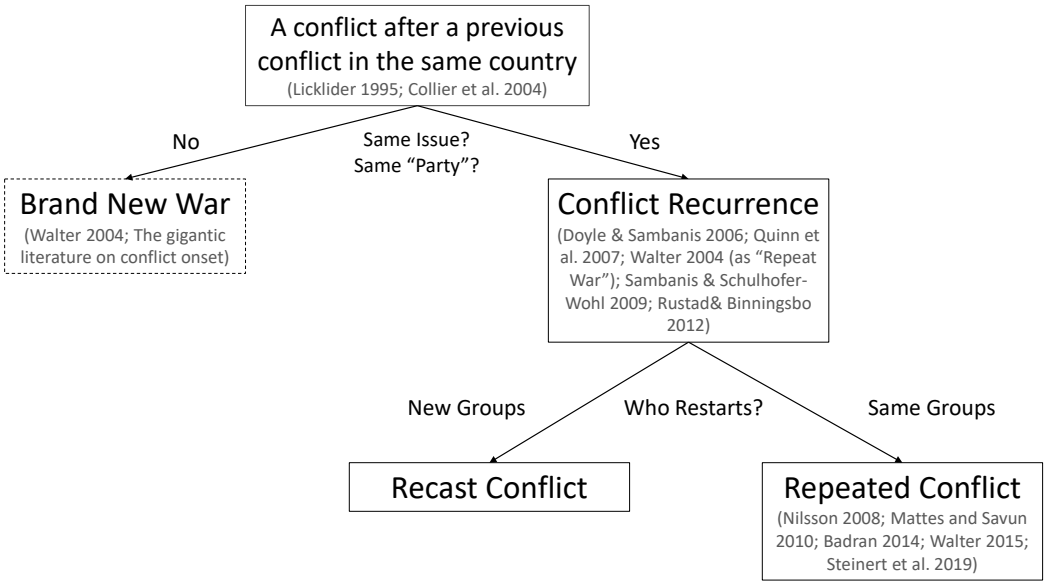
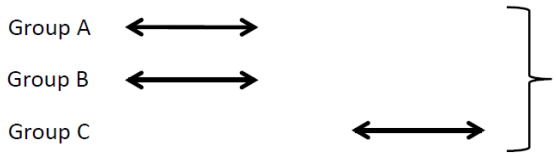


Figure 1: Categories of Conflict Recurrence

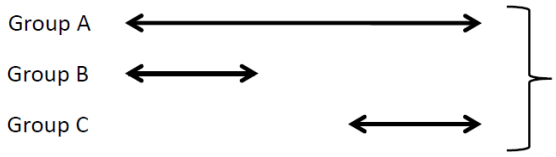
Figure 1 roughly describes the varieties of the concepts of conflict recurrence. Most studies focus on only one concept, discussing others in order to establish a single best concept for their purposes. This study and Walter (2004) include multiple concepts and focus on heterogeneity in them. However, as the discussion above and the figure clearly show, our coverage differs significantly. The partial peace approach uses conflict recurrence quite similar to the repeated conflict in this study. However, recast conflict is left outside of the scope.

[1]Zeigler employs two types of dependent variables: recur and recur_any. The latter solely relies on the ACD's incompatibility to define recurrence. The former is an alternative definition for the dependent variable. He inspects whether the recurred conflicts by the ACD coding rule involves actors that have significant linkage to the former rebel groups. Some may wonder what differentiates his coding of two types of conflict recurrence with mine. He uses connection between actors in previous and recurrent conflicts to identify if two conflicts share the same issue and should be coded as recurrence of the same conflict. However, he does not require that the same organizations fight recurrent war to be coded as recurrence. Therefore, his approach is more similar to Walter (2004), separating conflict recurrence and new war

There is another variant of partial peace: dyadic peace, where peace is defined on the dyadic relationship between two warring parties. Nilsson and Svensson (2021) employ the dyadic approach and take into account both the conflict recurrence when the same conflict dyad reemerges and when another conflict dyad emerges. They propose distinct mechanisms for the two types, where Islamic rebels affect the probability of dyadic conflict recurrence. This approach may involve measurement problems, however. In many multi-party civil wars, armed groups can come and go while the civil war itself is active (e.g. Guatemala in 1970s, Afghanistan in late 1980s, Chad in 1990s, etc.). In these cases, when one of many groups fighting left the battlefield and another group joined later, this may be coded as conflict recurrence with a new group. Since the war is on-going by other actors, this should be considered as shifts in active groups. Here, what causes this "recurrence" is likely related to the on-going war rather than how the "peace" goes.



This study	Recast conflict
Partial peace	Peace for A and B persists
Dyadic peace	Recast conflict



This study	On-going war (active groups rotated)
Partial peace	On-going war (active groups rotated)
Dyadic peace	Recast conflict with C (for the peace of B)

Figure 2: Comparison with Partial Peace Approaches

Figure 2 shows the differences between this study and partial peace approaches graphically. Here, the partial peace refers to that of Nilsson (2008) and the dyadic approach refers to that of Nilsson and Svensson (2021). In the top case, Group A and B stopped fighting at the same time and Group C started another conflict after a while. Since this case involves a time period where no group is fighting, all the approaches recognize this as peace. However, when Group C disturbs the peace, this study and the dyadic approach will code this as recast conflict while the partial peace does not consider this as conflict recurrence. In the bottom case, the conflict as a whole has been active since Group A continues fighting. Thus, this study and the partial peace do not code this as peace. Only the dyadic approach sees the peace between the government and Group B. When Group C joins the conflict, this study interprets it as a new rebel group joining the on-going war while the dyadic peace finds it a recurrent conflict breaking the peace of Group B. As I discussed above, I prefer the prior interpretation.

B Model Extensions

B.1 Analysis on the Model with a General Semi-concave Cumulative Density

Generalizing away from a particular distribution such as uniform, here I analyze the model in a quite general form. Recall Theorem **??**.

$$
\begin{aligned}
r^* &= \frac{1}{s}(\theta + c) f(\frac{r^*}{s} + l^* - \theta + \chi - \rho) \\
l^* &= (\theta + c) \left(f(\frac{r^*}{s} + l^* - \theta + \chi - \rho) + f(l^* - \theta + \chi) \right)
\end{aligned}
$$

General comparative statics can be derived by applying the implicit function theorem. Denote the two equations as follows.

$$
\begin{aligned}
I_R &= r - \frac{1}{s}(\theta + c) f(\frac{r^*}{s} + l^* - \theta + \chi - \rho) \\
I_L &= l - (\theta + c) \left(f(\frac{r^*}{s} + l^* - \theta + \chi - \rho) + f(l^* - \theta + \chi) \right)
\end{aligned}
$$

Then, the implicit function theorem guarantees that the comparative statics for a parameter x are given by,

$$
\begin{aligned}
\frac{\partial r}{\partial x} &= -\frac{\begin{vmatrix} \frac{\partial I_R}{\partial x} & \frac{\partial I_R}{\partial l} \\ \frac{\partial I_L}{\partial x} & \frac{\partial I_L}{\partial l} \end{vmatrix}}{\begin{vmatrix} \frac{\partial I_R}{\partial r} & \frac{\partial I_R}{\partial l} \\ \frac{\partial I_L}{\partial r} & \frac{\partial I_L}{\partial l} \end{vmatrix}} \\
\frac{\partial l}{\partial x} &= -\frac{\begin{vmatrix} \frac{\partial I_R}{\partial r} & \frac{\partial I_R}{\partial x} \\ \frac{\partial I_L}{\partial r} & \frac{\partial I_L}{\partial x} \end{vmatrix}}{\begin{vmatrix} \frac{\partial I_R}{\partial r} & \frac{\partial I_R}{\partial l} \\ \frac{\partial I_L}{\partial r} & \frac{\partial I_L}{\partial l} \end{vmatrix}}
\end{aligned}
$$

For simplicity, let F_r and F_l denote $F(\frac{r}{s} + l - \theta + \chi - \rho)$ and $F(l - \theta + \chi)$, respectively. The common denominator is then,

$$
D = \begin{vmatrix} \frac{\partial I_R}{\partial r} & \frac{\partial I_R}{\partial l} \\ \frac{\partial I_L}{\partial r} & \frac{\partial I_L}{\partial l} \end{vmatrix} = 1 - \frac{\theta + c}{s^2} f'_r \{1 - (\theta + c) f'_l\}
$$

where f_r and f_l denote the first order derivatives of F_r and F_l, respectively. f_r' and f_l' are the second order derivative.

Assume that F_r and F_l are semi-concave at the equilibrium. Given that the costs of goods are convex, this assumption is usually valid. As f_r' and f_l' are negative under the assumption, D is positive. Now, let me look into each parameter.

The nominators for $\frac{\partial r}{\partial \rho}$ and $\frac{\partial l}{\partial \rho}$ are,

$$N_{r\rho} = -\frac{(\theta+c)((\theta+c)f_l' - 1)f_r'}{s}$$
$$N_{l\rho} = (\theta+c)f_r'$$

Therefore, the comparative statics with respect to r and l are given as,

$$\frac{\partial r}{\partial \rho} = -\frac{N_{r\rho}}{D} \geq 0$$
$$\frac{\partial l}{\partial \rho} = -\frac{N_{l\rho}}{D} \geq 0$$

Next, the comparative statics with respect to the probabilities of wars can be calculated as,

$$\begin{aligned}
\frac{\partial P_R}{\partial \rho} &= -f_r(\frac{1}{s}\frac{\partial r}{\partial \rho} + \frac{\partial l}{\partial \rho} - 1) \\
&= -\frac{f_r s^2\left((\theta+c)f_l' - 1\right)}{s^2 - (s^2+1)\left(\theta+c\right)f_r' + (\theta+c)f_l'\left((\theta+c)f_r' - s^2\right)} \geq 0 \\
\frac{\partial P_L}{\partial \rho} &= -f_l\frac{\partial l}{\partial \rho} \\
&= \frac{f_l s^2(\theta+c)f_r'}{s^2 - (s^2+1)\left(\theta+c\right)f_r' + (\theta+c)f_l'\left((\theta+c)f_r' - s^2\right)} \leq 0
\end{aligned}$$

The results indicate that the government responds to an increased advantage of R by distributing more resources to both R and L. But as R gets more difficult to appease than L, P_R gets larger though mitigated by the increased r. Whereas, P_L decreases.

The results for s are as follows.

$$
\begin{aligned}
\frac{\partial r}{\partial s} &= \frac{\frac{1}{s}(\theta+c)(r(-1+(\theta+c)f_l')f_r' + sf_r(-1+(\theta+c)f_l'+(\theta+c)f_r'))}{D} \\
\frac{\partial l}{\partial s} &= \frac{-\frac{1}{s}(\theta+c)(rs+(\theta+c)f_r)f_r'}{D} \geq 0 \\
\frac{\partial P_R}{\partial s} &= \frac{1}{s^2}f_r\left(r - s(\frac{\partial r}{\partial s} + s\frac{\partial l}{\partial s})\right) \\
&= \frac{-\frac{1}{s}f_r\left(rs+(\theta+c)f_r\right)\left(-1+(\theta+c)f_l'\right)}{s^2-\left(s^2+1\right)(\theta+c)f_r' + (\theta+c)f_l'\left((\theta+c)f_r'-s^2\right)} \geq 0 \\
\frac{\partial P_L}{\partial s} &= -f_l\frac{\partial l}{\partial s} \\
&= \frac{\frac{1}{s}f_l(\theta+c)(rs+(\theta+c)f_r)f_r'}{s^2-\left(s^2+1\right)(\theta+c)f_r' + (\theta+c)f_l'\left((\theta+c)f_r'-s^2\right)} \leq 0
\end{aligned}
$$

The increased number of former rebel factions, interpreted as a decreased efficiency in private goods, does not necessarily decreases r while G puts more relative weights on public goods. As a result, P_R increases while P_L decreases.

The results for θ are here.

$$
\begin{aligned}
\frac{\partial r}{\partial \theta} &= \frac{s(f_r(-1+(\theta+c)f_l') - (\theta+c)(-1+f_l)f_r')}{D} \\
\frac{\partial l}{\partial \theta} &= \frac{s^2f_r + f_l(s^2-(\theta+c)f_r') + (\theta+c)(-s^2f_r' + f_l'(-s^2+(\theta+c)f_r')}{D} \geq 0 \\
\frac{\partial P_R}{\partial \theta} &= -f_r\left(\frac{1}{s}\frac{\partial r}{\partial \theta} + \frac{\partial l}{\partial \theta} - 1\right) \\
&= \frac{-f_r(-s^2+s^2f_l + f_r(1+s^2-(\theta+c)f_l'))}{s^2-\left(s^2+1\right)(\theta+c)f_r' + (\theta+c)f_l'\left((\theta+c)f_r'-s^2\right)} \\
\frac{\partial P_L}{\partial \theta} &= -f_l\left(\frac{\partial l}{\partial \theta} - 1\right) \\
&= \frac{-f_l(-s^2+s^2f_r + (\theta+c)f_r' + f_l(s^2-(\theta+c)f_r'))}{s^2-\left(s^2+1\right)(\theta+c)f_r' + (\theta+c)f_l'\left((\theta+c)f_r'-s^2\right)}
\end{aligned}
$$

The larger the stake is, the more G allocates resources to L. For other comparative statics, the signs dependent on the parameters.

Under the assumption of uniform distribution, we could establish $\frac{\partial P_R}{\partial \theta} \leq \frac{\partial P_L}{\partial \theta}$ (Corollary **??**). It is not generally the case here.

$$
\frac{\partial P_R}{\partial \theta} - \frac{\partial P_L}{\partial \theta} = \frac{s^2f_r - 2f_r^2 - s^2f_r^2 + (\theta+c)f_r^2f_l' - s^2f_l + 2(\theta+c)f_lf_r' + s^2f_l^2 - (\theta+c)f_l^2f_r'}{D}
$$

To get some intuition, let us explore a case. We can think of a case where $F_R = F_L$ as a benchmark.

In this case, the probabilities of two types of wars are the same. As $F_r = F_l$ implies $f_r = f_l$, by some algebra, the following relationship is confirmed.

$$\frac{\partial P_R}{\partial \theta} - \frac{\partial P_L}{\partial \theta} = \frac{-f_r^2 + (\theta + c) f_r f_r'}{D} \leq 0$$

Therefore, in this case, the prediction is the same as Corollary **??**.

Turning to the paremeter χ, the general comparative statics are,

$$\begin{aligned}
\frac{\partial r}{\partial \chi} &= \frac{s(\theta + c) f_r'}{D} \leq 0 \\
\frac{\partial l}{\partial \chi} &= -\frac{(\theta + c)(-s^2 f_r' + f_l'(-s^2 + (\theta + c) f_r'))}{D} \leq 0 \\
\frac{\partial P_R}{\partial \chi} &= -f_r \left(\frac{1}{s} \frac{\partial r}{\partial \chi} + \frac{\partial l}{\partial \chi} + 1 \right) \\
&= \frac{-s^2 f_r}{s^2 - (s^2 + 1)(\theta + c) f_r' + (\theta + c) f_l' ((\theta + c) f_r' - s^2)} \leq 0 \\
\frac{\partial P_L}{\partial \chi} &= -f_l \left(\frac{\partial l}{\partial \chi} + 1 \right) \\
&= \frac{-f_l (s^2 - (\theta + c) f_r')}{s^2 - (s^2 + 1)(\theta + c) f_r' + (\theta + c) f_l' ((\theta + c) f_r' - s^2)} \leq 0
\end{aligned}$$

The exogeneous cost for both R and L saves G some resources and makes the both types of wars more difficult. The results are consistent with the Corollary **??**.

Lastly, the comparative statics for c are derived as,

$$\begin{aligned}
\frac{\partial r}{\partial c} &= -\frac{s(f_r(-1 + (\theta + c) f_l') - (\theta + c) f_l f_r')}{D} \\
\frac{\partial l}{\partial c} &= \frac{s^2 f_r + f_l (s^2 - (\theta + c) f_r')}{D} \geq 0 \\
\frac{\partial P_R}{\partial c} &= -f_r \left(\frac{1}{s} \frac{\partial r}{\partial c} + \frac{\partial l}{\partial c} \right) \\
&= \frac{-f_r (s^2 f_l + f_r (1 + s^2 - (\theta + c) f_l'))}{s^2 - (s^2 + 1)(\theta + c) f_r' + (\theta + c) f_l' ((\theta + c) f_r' - s^2)} \leq 0 \\
\frac{\partial P_L}{\partial c} &= -f_l \left(\frac{\partial l}{\partial c} \right) \\
&= \frac{-f_l (s^2 f_r + f_l (s^2 - (\theta + c) f_r'))}{s^2 - (s^2 + 1)(\theta + c) f_r' + (\theta + c) f_l' ((\theta + c) f_r' - s^2)} \leq 0
\end{aligned}$$

Again, when we assume that $F_r = F_l$, the relative size of the impacts is shown to be,

$$\frac{\partial P_R}{\partial c} - \frac{\partial P_L}{\partial c} = \frac{-f_r}{D} \leq 0$$

and $\frac{\partial r}{\partial c}$ is easily shown to be positive. The cost of civil war perceived by the government encourages it to invest in both private and public goods to reduce the risk of wars. When the risks of the two types of wars are close enough, however, it suffers from the lack of access to potential rebels. While the government can reduce both types of risks, the risk of recast conflict is less affected by its effort.

B.2 Private Goods to Potential Rebels

One of the key modeling assumptions is that the government can provide private goods only to the former rebels. However, governments may extend their clientelistic network to the population with grievances in order to prevent another civil war. As I articulated in Section 1 of this paper, the provision of private goods to the former rebels is considered as easier than the private goods provision to the social group in general because the government can easily identify and reach the set of important recipients through the bargaining channel with the rebel organizations. However, it may be too extreme to assume that private goods provision is not possible toward the potential rebels. The government may know some social groups, militias, or goons that are specifically rebellious.

Therefore, in this section, I loosen the assumption that the private goods are only available to the former rebels. I instead assume that the private goods are less effective toward the local citizens. The first stage of the game has changed in the following manner.

Consider three actors: G, R, and L, denoting the government, former rebels and potential rebels, respectively. The game has two stages. In the first stage, the government allocates private goods to R (r_1) and to L (r_2) and public goods (l). Both R and L benefit from public goods.

The payoffs of R and L when they choose not to rebel are modified accordingly. R receives $\frac{r_1}{s} + l$ while L receives $\alpha r_2 + l$. Here, a parameter α is introduced to represent the effectiveness of private goods provision toward L. As the private goods toward potential rebels are less effective than toward the former rebels, $\alpha < \frac{1}{s}$.

Then, the lemma characterizing the decision should be,

Lemma A1 *Given the policies r_1, r_2, and l, the former rebels, R, start a repeated conflict if*

$$\theta + \epsilon_R - \chi + \rho > \frac{r_1}{s} + l$$

so the probability of a repeated conflict is

$$P_R(r_1, r_2, l) = 1 - F(\frac{r_1}{s} + l - \theta + \chi - \rho)$$

The potential rebels L start a recast conflict if

$$\theta + \epsilon_L - \chi > \alpha r_2 + l$$

so the probability of a recast conflict is

$$P_L(r_1, r_2, l) = 1 - F(\alpha r_2 + l - \theta + \chi)$$

The expected payoff for the government as a function of the policy is,

$$\mathbb{E}[U_G(r_1, r_2, l)] = B - \frac{r_1^2}{2} - \frac{r_2^2}{2} - \frac{l^2}{2} - (\theta + c)\left(2 - F(\frac{r_1}{s} + l - \theta + \chi - \rho) - F(\alpha r_2 + l - \theta + \chi)\right)$$

The government is constrained by the budget: $B - \frac{r_1^2}{2} - \frac{r_2^2}{2} - \frac{l^2}{2} \geq 0$.

Theorem A1 *The government's policies must satisfy the following conditions for an interior solution to be available.*

$$\begin{aligned}
r_1^* &= \frac{1}{s}(\theta + c) f(\frac{r_1^*}{s} + l^* - \theta + \chi - \rho) \\
r_2^* &= \alpha(\theta + c) f(\alpha r_2^* + l^* - \theta + \chi) \\
l^* &= (\theta + c)\left(f(\frac{r_1^*}{s} + l^* - \theta + \chi - \rho) + f(\alpha r_2^* + l^* - \theta + \chi)\right)
\end{aligned}$$

By assuming F to be uniform, I derive the corollaries in the following.

Corollary A1 *If the distribution F is uniform in the range $-\frac{1}{2\sigma}$ to $\frac{1}{2\sigma}$, then (interior) solutions characterized in Theorem A1 are*

$$\begin{aligned}
r_1^* &= \frac{\sigma}{s}(\theta + c) \\
r_2^* &= \alpha\sigma(\theta + c) \\
l^* &= 2\sigma(\theta + c)
\end{aligned}$$

and the equilibrium probabilities of repeated and recast conflicts are,

$$P_R^* = \frac{1}{2} - \sigma(-\theta + \frac{\sigma}{s^2}(\theta + c) + 2\sigma(\theta + c) + \chi - \rho)$$
$$P_L^* = \frac{1}{2} - \sigma(-\theta + \sigma\alpha^2(\theta + c) + 2\sigma(\theta + c) + \chi)$$

The comparative statics are driven accordingly. The parameters that affect r_2 are α, θ, and c. The comparative statics for other parameters do not change.

For the stakes of conflict (θ),

$$\frac{\partial P_R^*}{\partial \theta} = \sigma(1 - 2\sigma - \frac{\sigma}{s^2})$$
$$\frac{\partial P_L^*}{\partial \theta} = \sigma(1 - 2\sigma - \alpha^2\sigma)$$

Given $\alpha < \frac{1}{s}$, Corollary 3 does not change ($\frac{\partial P_R^*}{\partial \theta} < \frac{\partial P_L^*}{\partial \theta}$).

In terms of the government's cost of fighting (c),

$$\frac{\partial P_R^*}{\partial c} = -\sigma^2(\frac{1}{s^2} + 2)$$
$$\frac{\partial P_L^*}{\partial c} = -\sigma^2(\alpha^2 + 2)$$

Therefore, prediction over the direction of effects is not different from Corollary 6.

For the additional parameter α itself, the following prediction is drawn.

$$\frac{\partial P_R^*}{\partial \alpha} = 0$$
$$\frac{\partial P_L^*}{\partial \alpha} = -2\sigma^2\alpha(\theta + c)$$

This corollary dictates that the increased effectiveness of private goods toward potential rebels will decrease the probability of recast conflict. This is a natural prediction given that the government has an additional channel for appeasement.

Overall, this additional channel of appeasement has few impacts on the conclusion presented in the main article. The only significant difference is observed in the prediction about the effects of conflict stakes. Originally, though the government has stronger incentives to appease both potential and former rebels, they face difficulty in appeasing potential rebels because of the lack of channels. This difficulty is mitigated by the private goods provision to the potential rebels. Thus, the difference between the two

effects get smaller.

C Descriptive Statistics

Table 1 describes the independent variables in the main model. Though some of the variables are time-variant, the descriptive statistics here are calculated for the first period of each observation.

Table 1: Descriptive Statistics of Independent Variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Victory	195	0.179	0.385	0	0	0	1
Agreement	195	0.169	0.376	0	0	0	1
PKO	195	0.144	0.352	0	0	0	1
Revolution	195	0.477	0.501	0	0	1	1
Num_Actor	195	1.262	0.526	1	1	1	4
Res_Conf	195	0.559	0.498	0	0	1	1
ELF	195	0.612	0.198	0.095	0.497	0.766	1.000
Mountain	195	23.203	22.038	0.000	6.900	35.600	81.000
Post_CW	195	0.754	0.432	0	1	1	1
lag_Growth	195	0.027	0.149	−0.568	−0.013	0.080	0.509
lag_IMR	195	70.854	40.076	4.300	42.050	95.500	213.300

Figures 3, 4, and 5 are estimated survival functions by the Kaplan-Meier method. Figure 3 is the pooled survival function that does not differentiate the two types. Figures 4 and 5 correspond to survival functions of repeated conflicts and recast conflicts, respectively. These simple descriptions clearly indicate that the probability of repeated conflicts is very high immediately after wars. However, it soon declines while the possibility of recast conflicts seems to be constant over time, consistent with Hypothesis 4.

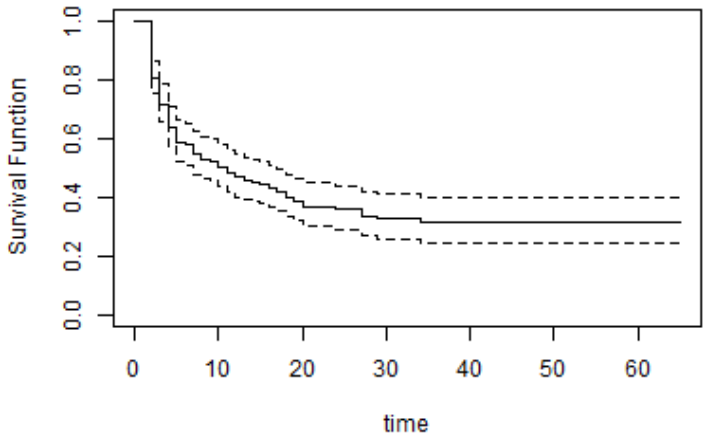


Figure 3: KM plot for the pooled survival function

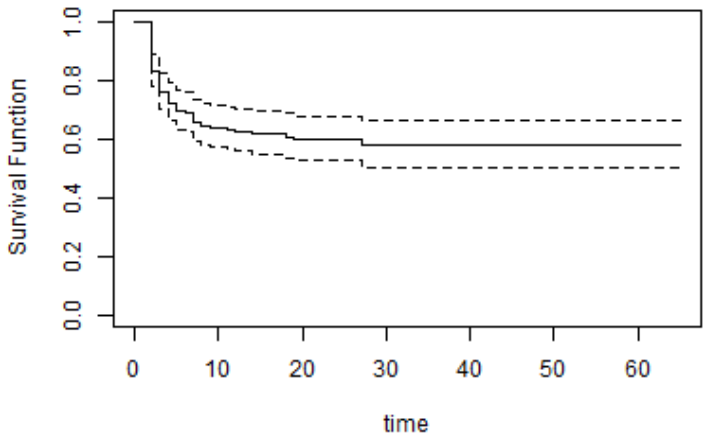


Figure 4: KM plot for the repeat specific survival function

D Effects of Variables on Cumulative Incidence Functions

In the following, the substantive effects of each variable on cumulative incidence functions are estimated. They are calculated by fixing the other variables at their median. 90% confidence intervals are obtained from quantile bootstrapping. All the results are obtained from the main model. Regarding continuous variables, estimation is done for 25% and 75% quantiles. My discussion mainly focuses on the significant variables here.

The number of former rebel groups has large effects on the cause-specific hazard for repeated conflicts while it has little effects on recast conflicts. This causes a jump in the cumulative incidence of repeated conflicts. At the same time, the CIF for recast conflicts is decreased. This is a result of indirect effects, that is, the probability for recast conflicts is increased by the decreased probability for repeated conflicts. We have, however, not observed direct effects of the number of actors on recast conflicts.

A revolutionary characteristic indicates very strong and significant opposite effects for repeated and recast conflicts. Territorial conflicts enormously increase the probability of repeated conflicts while decreasing that of recast conflicts by more than half.

Resource conflicts are correlated with higher probability of recast conflicts. In resource conflicts, the hazard of recast conflicts is more than double that of non-resource conflicts. This results in a strong jump in the cumulative incidence of recast conflicts.

PKOs' effects on the CIFs are very large for repeated conflicts. It is large for recast conflicts as well, though it is not significant.

IMR indicates a strong effect on the hazard of recast conflicts. A change of IMR from 43 to 97

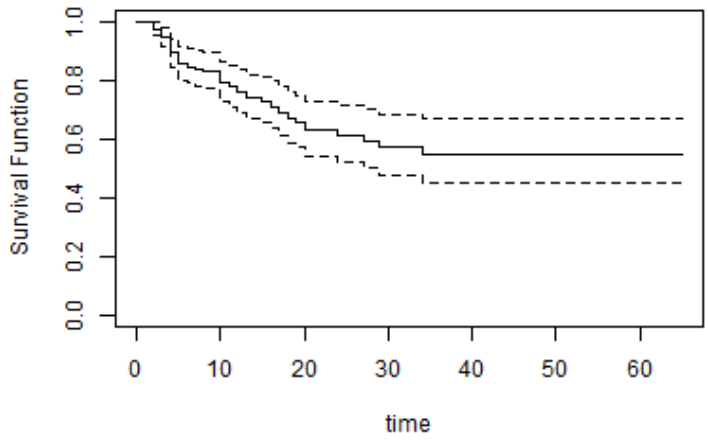


Figure 5: KM plot for the recast specific survival function

doubles the risk of recast conflicts consistent with my hypothesis and Walter (2004)'s finding. Though insignificant, IMR seems to decrease the hazard of repeated conflicts.

Government victory largely decreases both the hazard function and the CIF for repeated conflicts. This results in increased CIF for recast conflicts. However, we should not confuse this as a direct effect on recast conflicts.

Figure 6: Effects of the Number of Groups

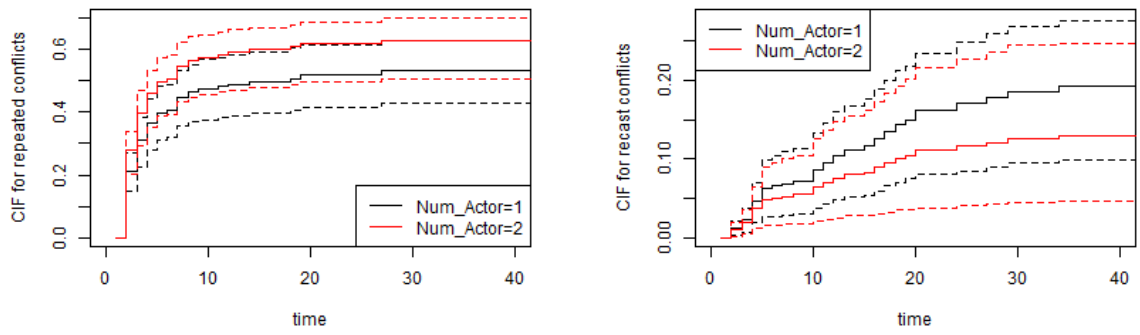


Figure 7: Effects of Revolutionary Incompatibility

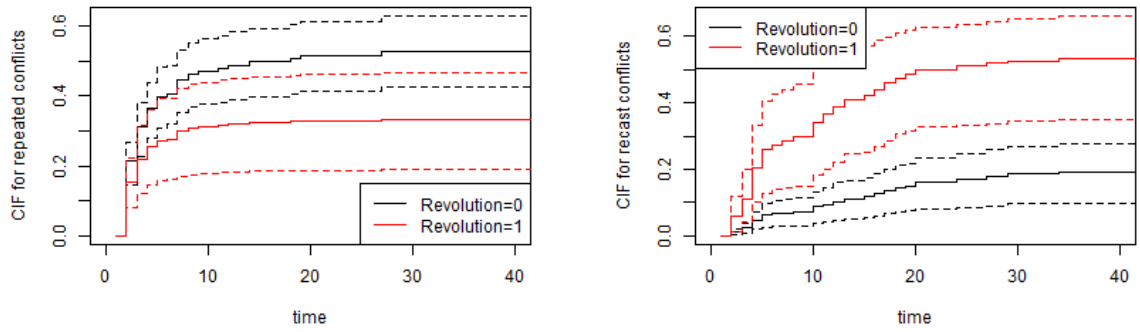


Figure 8: Effects of Resource Conflict

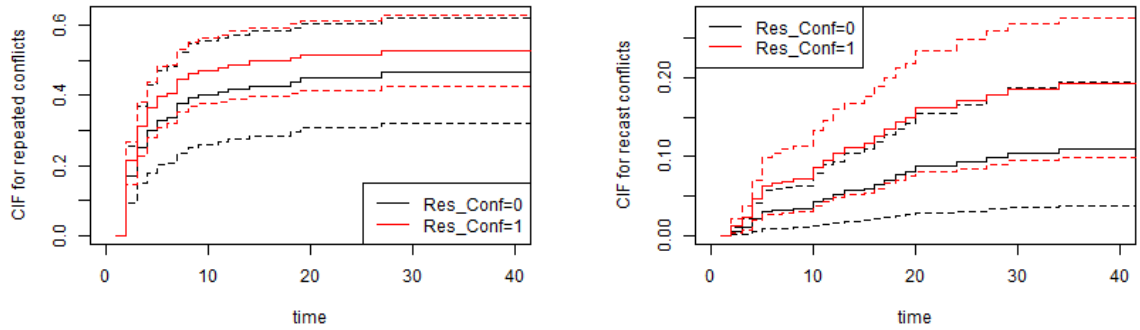


Figure 9: Effects of PKO

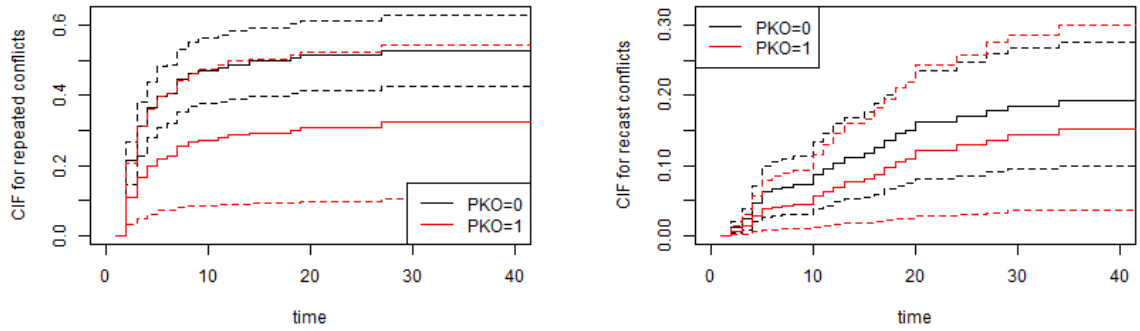


Figure 10: Effects of Mountainous Terrains

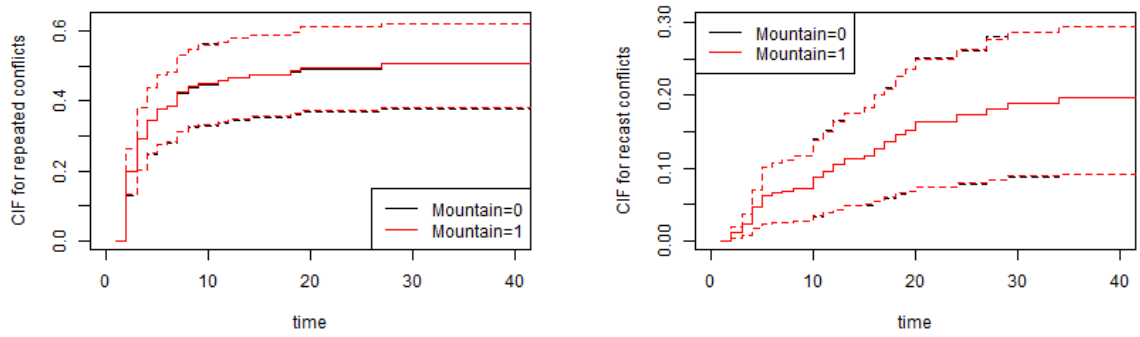


Figure 11: Effects of Infant Mortality Ratio

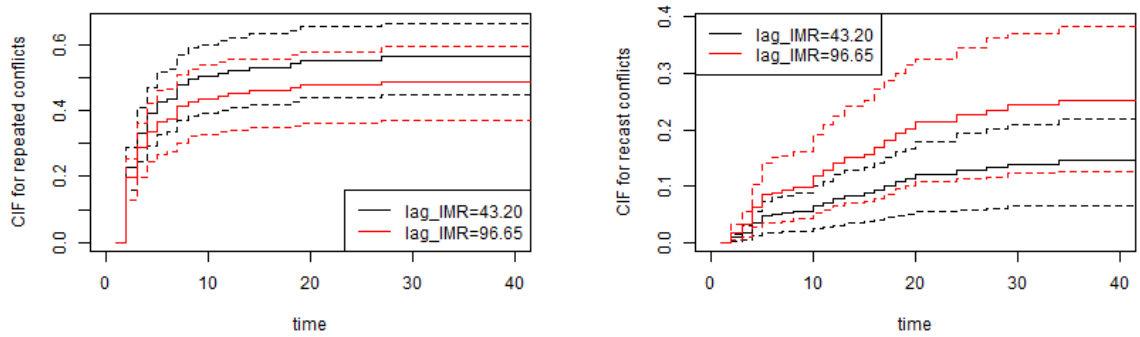


Figure 12: Effects of Ethno-linguistic Fractionalization

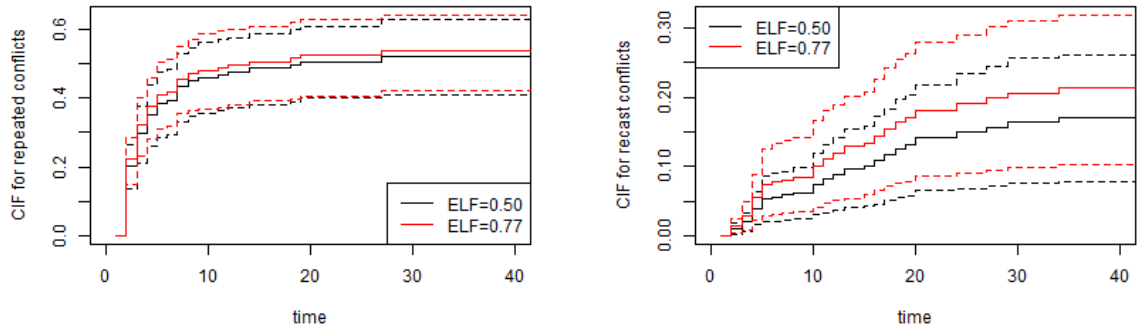


Figure 13: Effects of Government Victory

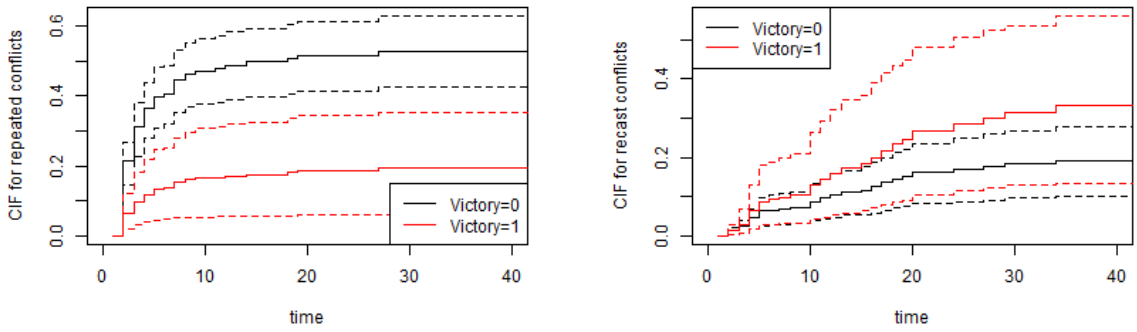


Figure 14: Effects of GDP Growth

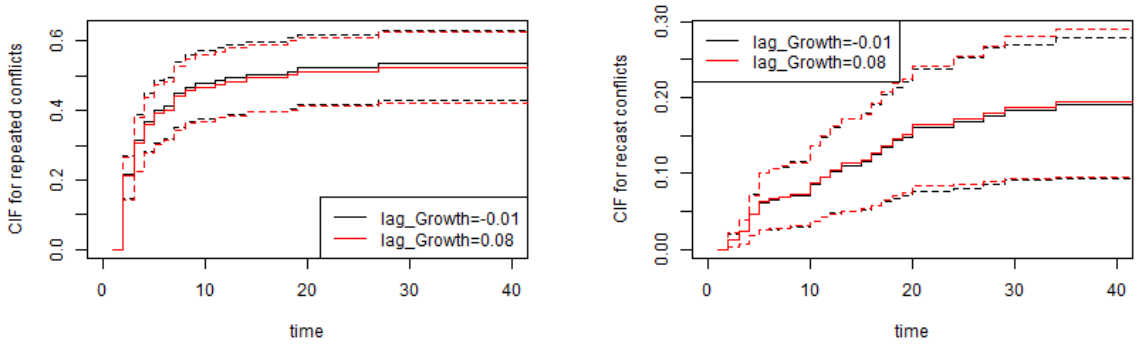


Figure 15: Effects of Peace Agreement

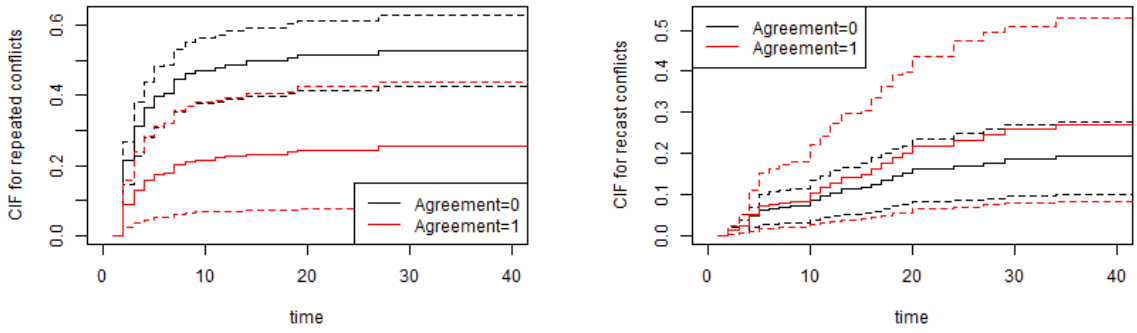
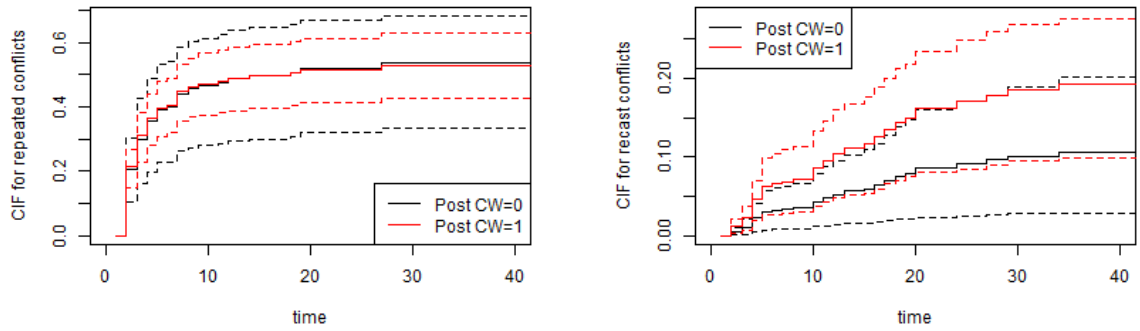


Figure 16: Effects of Post Cold War



E Alternative Specification/Dependent Variables

E.1 More Coherent Conflict IDs with Zeigler's Coding

This section uses alternative definitions for the dependent variable. Some of the cases of recast conflicts can be seen not as recurred conflicts but as new conflicts. Zeigler (2016) employs two types of dependent variables: recur and recur_any. The latter solely relies on the ACD's incompatibility to define recurrence. The former is an alternative definition for the dependent variable. He inspects whether the recurred conflicts by the ACD coding rule involves actors that have significant linkage to the former rebel groups. This seems to be efficient in excluding irrelevant wars. I utilize his code. Some of the cases in my sample are not present in Zeigler's data. This is due to the difference in versions of the ACD. I apply the coding rule to those cases (denoted as Zeigler+). Table 2 presents the results for regressions with the refined dependent variables using Zeigler's coding rule.

E.2 Conflict Recurrence by Splinter Groups as Repeated Conflict

Splinter groups may violate the assumption in the model that the potential rebels are weaker than the former ones since they may have access to the legacy of former rebels. However, this concern is not likely to influence the empirical analysis. The frequency of conflict recurrence triggered by splinter organizations is depicted in Figure 17. The data indicate that these cases are quite marginal. However, we should never dismiss splinters as a risk for conflict recurrence. The UCDP data used in this study require a peace spell to be longer than one year to be recognized as peace. It is possible and likely that splinter recurrence happens within one year after the termination of former rebellion because splinters may have a sufficient strength to break the peace immediately.

Table 3 reports regression results when I recode conflict recurrence by splinters as repeated conflict.

Table 2: Main Model with Zeigler's Codes

	Zeigler			Zeigler+		
	Pooled	Repeated	Recast	Pooled	Repeated	Recast
Num_Actor	0.28	0.41*	0.01	0.29*	0.39*	0.11
	(0.17)	(0.22)	(0.31)	(0.17)	(0.22)	(0.31)
Revolution	0.27	−0.35	1.42***	0.26	−0.26	1.29***
	(0.22)	(0.30)	(0.39)	(0.23)	(0.30)	(0.41)
Res_Conf	0.53**	0.31	0.86**	0.52**	0.31	0.89**
	(0.24)	(0.31)	(0.38)	(0.25)	(0.31)	(0.42)
PKO	−0.74**	−0.84*	−0.77	−0.72**	−0.86*	−0.69
	(0.35)	(0.50)	(0.54)	(0.35)	(0.50)	(0.55)
Mountain	0.01	0.01	0.01	0.01	0.01	0.01
	(0.004)	(0.01)	(0.01)	(0.005)	(0.01)	(0.01)
lag_IMR	0.002	−0.004	0.01**	0.002	−0.004	0.01**
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)
ELF	0.89	0.49	1.89*	0.80	0.39	2.00*
	(0.57)	(0.71)	(0.99)	(0.58)	(0.71)	(1.08)
Victory	−0.72**	−1.31***	−0.10	−0.81***	−1.31***	−0.18
	(0.30)	(0.50)	(0.39)	(0.31)	(0.49)	(0.43)
lag_Growth	−0.30	−0.38	0.07	0.01	−0.41	1.46
	(0.87)	(1.05)	(1.39)	(0.88)	(1.05)	(1.49)
Agreement	−0.64*	−1.10**	−0.23	−0.65**	−1.13**	−0.19
	(0.33)	(0.50)	(0.48)	(0.33)	(0.50)	(0.50)
Post_CW	0.36	0.05	0.80*	0.36	0.07	0.84*
	(0.27)	(0.34)	(0.47)	(0.28)	(0.34)	(0.50)
N	2665	2665	2665	2602	2602	2602
Log Likelihood	−521.65	−328.65	−177.94	−500.91	−326.90	−159.40
LR Test (df = 11)	39.75***	37.66***	36.51***	39.20***	36.22***	36.59***

***p < .01; **p < .05; *p < .1

Results are highly robust against this alternative coding.

E.3 Rebel Victory Included

Regression results with rebel victory cases included in the dataset are reported in Table 4. The results do not change from the main analysis.

Table 3: When Splinter Recurrence is Coded As Repeated

	Pooled	Repeated	Recast
Number of Groups	0.25	0.38*	−0.01
	(0.17)	(0.21)	(0.31)
Revolution	0.33	−0.37	1.82***
	(0.22)	(0.28)	(0.43)
Resource Conflict	0.55**	0.33	1.04***
	(0.23)	(0.30)	(0.39)
PKO	−0.75**	−1.07**	−0.31
	(0.35)	(0.50)	(0.53)
Mountain	0.01	0.00	0.01
	(0.00)	(0.01)	(0.01)
lag IMR	0.00	−0.00	0.01*
	(0.00)	(0.00)	(0.00)
ELF	0.86	0.61	1.44
	(0.55)	(0.70)	(0.97)
Victory	−0.63**	−1.07**	−0.17
	(0.27)	(0.43)	(0.37)
lag Growth	−0.34	−0.27	−0.60
	(0.86)	(1.05)	(1.48)
Peace Agreement	−0.65**	−0.61	−0.77
	(0.32)	(0.41)	(0.56)
Post Cold War	0.40	0.23	0.59
	(0.27)	(0.33)	(0.45)
Observations	2,832	2,832	2,832
Log Likelihood	−550.39	−362.52	−172.57
LR Test (df = 11)	40.77***	38.04***	37.46***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 4: Rebel Victory Included

	Pooled	Repeated	Recast
Number of Groups	0.23	0.44**	−0.06
	(0.17)	(0.22)	(0.29)
Revolution	0.45**	−0.34	1.68***
	(0.21)	(0.29)	(0.37)
Resource Conflict	0.71***	0.33	1.21***
	(0.23)	(0.31)	(0.35)
PKO	−0.68**	−0.85*	−0.66
	(0.34)	(0.50)	(0.49)
Mountain	0.00	0.01	0.00
	(0.00)	(0.01)	(0.01)
lag IMR	0.00	−0.00	0.01**
	(0.00)	(0.00)	(0.00)
ELF	0.64	0.47	0.92
	(0.52)	(0.71)	(0.83)
Victory	−0.62**	−1.61***	0.04
	(0.25)	(0.49)	(0.33)
lag Growth	−0.09	−0.39	0.29
	(0.83)	(1.05)	(1.21)
Peace Agreement	−0.69**	−1.09**	−0.32
	(0.32)	(0.50)	(0.47)
Post Cold War	0.35	0.04	0.67*
	(0.26)	(0.34)	(0.40)
Observations	3,121	3,121	3,121
Log Likelihood	−578.37	−330.20	−224.55
LR Test (df = 11)	44.64***	47.53***	49.14***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

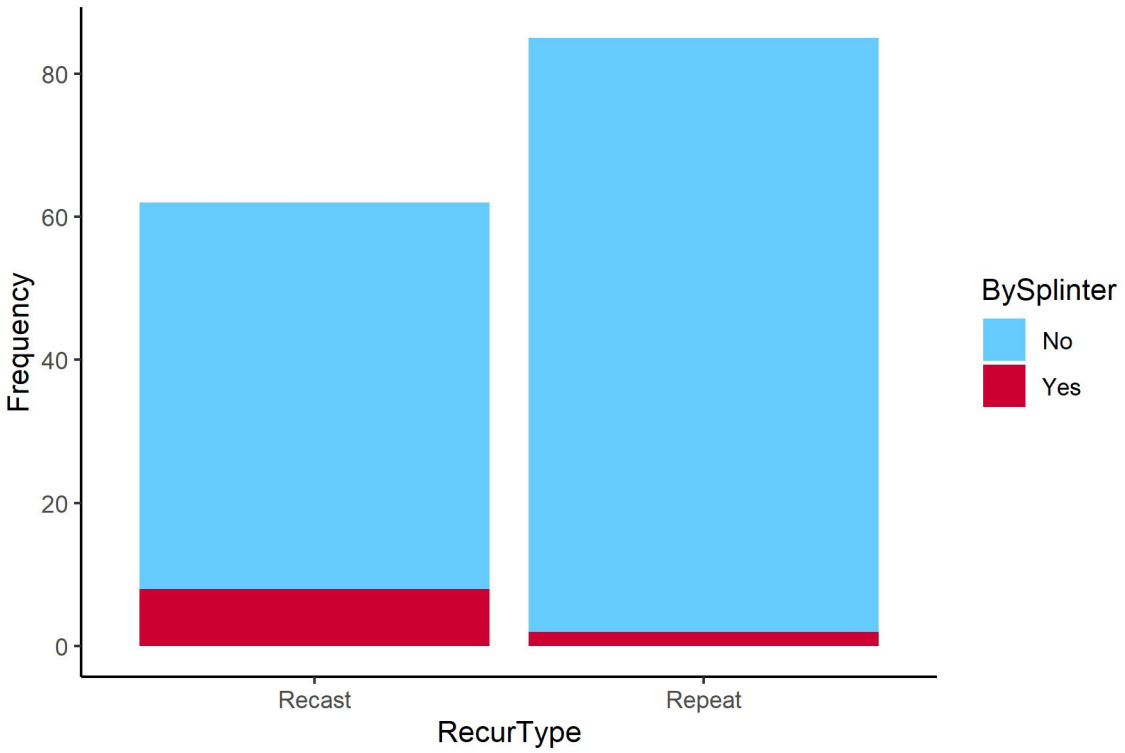


Figure 17: Splinter recurrence is not frequent

E.4 Different Intervals to Define Conflict Termination

To measure the end of conflict (or post-conflict peace), time periods with no or little violence are often employed. Kreutz and the UCDP Conflict Termination dataset uses one year interval of violence. However, many argue that the interval is too short and confusing less intense periods as peace especially for smaller wars (e.g. Gates and Strand 2004; Rustad & Binningsbø 2012; Uzonyi and Hanania 2017).

Here, I employ two years and three years intervals for robustness checks. But we should note the finding about the baseline hazards of repeated and recast conflicts. Since repeated conflicts are more concentrated on the initial periods of peace, coding decisions on the interval will shift the weight of the two types of conflict recurrence.

Table 5 shows the results using two and three years of interval. As you can see in the number of events, the proportion of repeated and recast conflicts shifts when we vary the interval. This is another important insight the distinction between repeated and recast conflict provides when we interpret quantitative evidence on conflict recurrence. Decisions on the length of intervals have a meaning more than increasing or decreasing measurement error. When you set the interval longer, it means you weigh recast conflict more in your hypothesis testing or prediction.

Compared to the main result in Table **??**, the pooled model gets more similar to that for recast conflict when we take a longer interval. However, the results for repeated and recast conflicts are largely

Table 5: Main Model with Different Interval

	Two Years			Three Years		
	Pooled	Repeated	Recast	Pooled	Repeated	Recast
Number of Groups	0.40*	0.77***	0.06	0.17	0.20	0.20
	(0.21)	(0.29)	(0.32)	(0.29)	(0.55)	(0.35)
Revolution	0.54**	−0.09	1.29***	0.85***	0.10	1.38***
	(0.27)	(0.40)	(0.41)	(0.31)	(0.48)	(0.43)
Resource Conflict	0.93***	0.96**	0.97**	0.89***	0.85	0.96**
	(0.29)	(0.45)	(0.39)	(0.31)	(0.54)	(0.40)
PKO	−0.85**	−1.05	−0.81	−0.81*	−0.88	−1.04
	(0.41)	(0.66)	(0.56)	(0.47)	(0.80)	(0.63)
Mountain	0.00	0.01	0.00	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lag IMR	−0.00	−0.01**	0.01	0.00	−0.02**	0.01*
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
ELF	1.17*	0.32	1.84*	1.59**	1.52	1.48
	(0.66)	(0.93)	(0.99)	(0.75)	(1.19)	(1.03)
Victory	−0.30	−0.95*	0.10	−0.20	−0.63	0.06
	(0.29)	(0.55)	(0.37)	(0.31)	(0.60)	(0.38)
lag Growth	−1.12	−0.25	−1.39	−0.18	1.69	−0.64
	(1.15)	(1.74)	(1.50)	(1.30)	(2.12)	(1.57)
Peace Agreement	−0.35	−0.98	0.08	−0.38	−1.81*	0.13
	(0.38)	(0.66)	(0.51)	(0.44)	(1.08)	(0.55)
Post Cold War	0.26	−0.24	0.56	0.30	−0.50	0.69
	(0.31)	(0.46)	(0.44)	(0.35)	(0.54)	(0.46)
Events	83	39	44	66	26	40
Units	179	179	179	161	161	161
Observations	2,757	2,757	2,757	2,704	2,704	2,704
Log Likelihood	−363.56	−169.41	−179.67	−282.19	−109.90	−159.90
LR Test (df = 11)	33.23***	30.74***	33.82***	27.00***	20.18**	33.24***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

consistent with the model with one year interval. A difference to note is that the results in Table 5 indicate that the infant mortality ratio (IMR) indicates a strong negative correlation with the risk of repeated conflict. This is potentially a very important finding because it means that economic improvement may encourage the former rebels to go back to war (while it prevents potential ones from waging a war). My model did not predict this, and thus, I cannot provide a clear explanation for this.

E.5 Major Civil Wars Only

UCDP datasets include many minor conflicts in them. The possibility that mechanisms of conflict recurrence may vary between major and minor wars is worth investigating.

Table 6 reports the results when I divide the sample into major and minor wars (I use the cumulative intensity in UCDP dataset). It shows that major conflicts involve a higher proportion of repeated conflict. The results are largely consistent to the main results. However, though the effect is consistent with the prediction, the number of groups lost statistical significance. And mountainous terrain indicates significant positive effects. This variable may be confounded by the size of a country (implying the size of war), though. Minor conflicts are less frequent in the data and include recast conflicts more. Then, the model for repeated conflict does not provide statistically discernible patterns while the result for recast conflict is highly consistent to the main result.

E.6 Other Estimation Approaches

Rather than assuming hazard proportionality on cause-specific hazards, we can assume a proportionality on subdistribution hazards. In proportional subdistribution hazard models, we stop the counting processes of a unit when it experiences competing events. For example, when we analyze repeated conflicts, units that experience recast conflicts are stopped right before the events. The stopped units are considered to survive infinitely with respect to repeated conflicts. By doing so, we can construct subdistributional processes, in which survival time can be written as,

$$\theta_k = \begin{cases} T(X_T = k) \\ \infty(X_T \neq k) \end{cases}$$

Where θ_k denotes the survival time in a subditributional process for cause k. T denotes time where a unit experiences any event (or death) and X_T denotes what kind of events it experiences at time T. The distribution function of θ_k is the same as the cumulative incidence function for cause k.

$$P(\theta_k \leq t) = P(T \leq t, X_T = 1) for all t$$

Table 6: Major and Minor Conflicts

	Major Conflict			Minor Conflict		
	Pooled	Repeated	Recast	Pooled	Repeated	Recast
Number of Groups	0.08	0.36	−0.25	0.35	0.50	−0.24
	(0.21)	(0.25)	(0.39)	(0.37)	(0.48)	(0.71)
Revolution	0.37	−0.23	2.17***	0.54	−0.71	2.40***
	(0.27)	(0.33)	(0.64)	(0.49)	(0.68)	(0.78)
Resource Conflict	0.12	−0.27	1.40**	1.15**	1.10	2.25***
	(0.31)	(0.37)	(0.65)	(0.53)	(0.78)	(0.82)
PKO	−0.42	−0.77	0.04	−1.17*	−0.59	−2.18*
	(0.46)	(0.70)	(0.69)	(0.63)	(0.80)	(1.28)
Mountain	0.01*	0.01**	0.02*	−0.00	−0.02	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
lag IMR	0.01	0.00	0.01	−0.00	−0.02*	0.02*
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
ELF	0.64	−0.26	2.90**	0.96	1.19	−0.50
	(0.68)	(0.81)	(1.44)	(1.02)	(1.53)	(1.65)
Victory	−1.18***	−2.29***	−0.38	−0.32	−0.59	0.57
	(0.38)	(0.77)	(0.52)	(0.42)	(0.68)	(0.62)
lag Growth	−1.15	−0.74	−2.21	0.46	−0.23	2.41
	(1.10)	(1.22)	(2.06)	(1.51)	(2.24)	(2.57)
Peace Agreement	−1.30***	−1.60**	−0.98	0.18	−0.31	0.75
	(0.46)	(0.67)	(0.71)	(0.48)	(0.82)	(0.66)
Post Cold War	0.73*	0.73	0.05	0.10	−0.90*	1.91**
	(0.38)	(0.51)	(0.64)	(0.40)	(0.53)	(0.81)
Events	68	44	24	52	27	25
Units	129	129	129	89	89	89
Observations	1,735	1,735	1,735	1,097	1,097	1,097
Log Likelihood	−268.22	−173.14	−78.69	−194.15	−99.49	−81.22
LR Test (df = 11)	36.85***	39.81***	32.40***	17.52*	20.27**	25.99***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

The subdistribution hazard is defined as,

$$\lambda_k(t)dt \equiv P(\theta \in dt | \theta \geq t)$$

Modeling λ in the same way as the Cox proportional hazard model, we can estimate the coefficients that are directly linked to the CIFs. For more detail, see Beyersmann et al. (2012).

Table 7: Results from the Proportional Subdistribution Hazard Model

	Pooled "	Repeated	Recast
Number of Groups	0.25	0.46**	−0.35
	(0.17)	(0.22)	(0.27)
Revolution	0.33	−0.54*	1.66***
	(0.22)	(0.29)	(0.38)
Resource Conflict	0.55**	0.21	0.89**
	(0.23)	(0.30)	(0.37)
PKO	−0.75**	−0.80	−0.63
	(0.35)	(0.51)	(0.50)
Mountain	0.01	0.01	0.01
	(0.00)	(0.01)	(0.01)
lag IMR	0.00	−0.00	0.01**
	(0.00)	(0.00)	(0.00)
ELF	0.86	0.34	1.40
	(0.55)	(0.73)	(0.91)
Victory	−0.63**	−1.31***	0.56
	(0.27)	(0.50)	(0.35)
lag Growth	−0.34	−0.26	−0.01
	(0.86)	(1.07)	(1.36)
Peace Agreement	−0.65**	−1.06**	0.17
	(0.32)	(0.50)	(0.45)
Post Cold War	0.40	0.08	0.81**
	(0.27)	(0.34)	(0.41)
Observations	2,832	3,887	4,274
Log Likelihood	−550.39	−335.26	−221.26
LR Test (df = 11)	40.77***	40.87***	42.04***
Notes:	***Significant at the 1 percent level.		
	**Significant at the 5 percent level.		
	*Significant at the 10 percent level.		

In this analysis, censoring is administratively decided, that is, units that survive until 2005 will be censored. The units experiencing recast conflicts are considered to survive until the end of observation in repeated conflict regressions for computational purposes. Cox proportional hazard estimation using this reshaped dataset can generate coefficients for proportional subdistribution hazard models. Subdistribution hazard models allow probabilistic interpretation because the subdistribution hazards are directly linked to CIFs. Table 7 shows the result. The results are mostly the same as the main results in terms

of statistical significance.

I prefer the Cox proportional hazard models to parametric ones to estimate the coefficients for each variable because we do not have a theoretical expectation about which stochastic process the conflict recurrence will follow. I have a hypothesis about the shape of hazard functions, that the risk of repeated conflict is initially high but wanes overtime while that of recast conflict should be rather constant. Although I tested this graphically by looking at the baseline hazard functions in the main analysis, I can statistically test this if I allow parametric assumptions.

Table 8 reports the results from a competing risk Weibull regression. The reported coefficients are regression coefficients. Positive values indicate a *lower* risk in this case. The results are basically robust.

The shape parameter at the bottom represents the shape of the estimated baseline Weibull function. If the parameter is 1, it means that the hazard is constant over time. A value from 0 to 1 forms a decreasing hazard while values over 1 is associated with an increasing hazard. It can never take a negative value. Thus, the statistical tests are done against the null of 1. The risk for repeated conflict indicates strong and significant decreasing trends while that of recast conflict is slightly increasing. This is consistent with the cumulative incidence functions in Figure **??**.

Instead of survival analysis, I can estimate the model with a multinomial logistic regression, which is more canonical. I estimate a logistic regression with controlling first, second, and third order polynomial of peace duration. Table 9 reports the results. They are almost completely consistent with the main results.

Table 8: Results from Competing Risk Weibull Regression

	Pooled	Repeated	Recast
Number of Groups	−0.48**	−0.91***	−0.12
	(0.19)	(0.32)	(0.21)
Revolution	−1.04***	−0.15	−1.82***
	(0.28)	(0.47)	(0.36)
Resource Conflict	−1.81***	−2.01***	−1.55***
	(0.29)	(0.47)	(0.31)
PKO	1.00**	1.10	0.75
	(0.45)	(0.78)	(0.45)
Mountain	−0.00	−0.00	−0.00
	(0.01)	(0.01)	(0.01)
lag IMR	−0.01***	−0.01	−0.01***
	(0.00)	(0.01)	(0.00)
ELF	0.26	0.81	−0.39
	(0.61)	(0.94)	(0.72)
Victory	1.51***	3.03***	0.42
	(0.31)	(0.72)	(0.27)
lag Growth	0.13	0.03	0.27
	(0.98)	(1.68)	(0.97)
Peace Agreement	0.24	0.91	−0.18
	(0.41)	(0.77)	(0.41)
Post Cold War	−0.16	−0.08	−0.13
	(0.31)	(0.49)	(0.34)
Constant	8.44***	9.26***	8.93***
	(0.68)	(1.04)	(0.91)
shape	0.88*	0.72***	1.28*
	(0.07)	(0.07)	(0.15)
Observations	2,832	2,832	2,832
Log Likelihood	−756.22	−470.04	−339.05
χ^2 (df = 11)	129.91***	90.24***	89.13***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 9: Results from a Multinomial Logit

	Repeated	Recast
Number of Groups	0.46^{**}	-0.01
	(0.22)	(0.28)
Revolution	$-$ 0.32	1.56^{***}
	(0.27)	(0.41)
Resource Conflict	0.37	0.97^{***}
	(0.32)	(0.36)
PKO	-0.90^{*}	-0.84
	(0.54)	(0.64)
Mountain	0.01	0.01
	(0.01)	(0.01)
lag_IMR	-0.004	0.01^{**}
	(0.003)	(0.005)
ELF	0.53	1.60^{*}
	(0.68)	(0.89)
Victory	-1.44^{***}	-0.08
	(0.47)	(0.37)
lag_Growth	-0.08	0.004
	(0.93)	(1.58)
Peace Agreement	-1.12^{*}	-0.22
	(0.58)	(0.46)
Post Cold War	0.10	0.82^{*}
	(0.33)	(0.42)
time	-0.12	0.09
	(0.10)	(0.09)
time^2	-0.004	-0.003
	(0.01)	(0.01)
time^3	0.0001	-0.0000
	(0.0001)	(0.0001)
Intercept	-3.15^{***}	-6.37^{***}
	(0.71)	(0.98)

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .1$

F Sensitivity Analysis of Model Specification

My main analysis tries to examine multiple hypotheses at the same time, making a fine-tuned controls infeasible. In stead of discussing what should be a good specification for those many variables, I employ a bruteforce approach using Bayesian model averaging (BMA) technique. It allows us to explore the entire model space and weigh each model by its Bayes factor[2]. By applying it, I can relativize the coefficients reported in Table **??** with respect to all the potential variables to be considered in the model. I added 10 additional variables for exploration: logged death tolls and duration of former conflicts, rebel fragmentation in them other ongoing conflicts in the same country or neighboring countries (the author constructs all of them from UCDP), logged GDP per capita and population (from Gleditsch et al. 2002), regime types (from Polity IV), inter-ethnic economic inequality (Buhaug et al. 2014).

Figures 18 to 23 demonstrate the results using Akaike Information Criterion (AIC) as the estimator of the Bayes factor. The curved lines represent the posterior distribution of coefficients for each variable while the vertical lines indicate the probability that a model including the variable is rejected by the information criterion. Victory, agreements, PKOs, revolution, and the number of actors are very strong predictors for repeated conflict, with high probability of models including them and large coefficients. fragmentation of rebels, ELF, democracy, and IMR are weaker ones. With respect to recast conflicts, revolution, battle-related deaths, resource conflict, post-Cold War, and IMR are very strong predictors. PKOs, fragmentation, population, and ELF are secondary ones. For strong predictors, the results are generally consistent with my argument and the results of the main analysis.

Figures 24 to 29 present the results using Bayesian Information Criterion (BIC). Since BIC generally favors more parsimonious models than AIC, only very strong predictors are selected and many variables are rejected. The results are consistent with my main results but the robustness of the coefficients of weaker factors is doubtful using this procedure. However, this is more likely to be the results from poor measurements and small sample size than insignificance of the coefficients. BIC may be too strict to be employed in global comparisons of armed conflict. In fact, Montgomery et al. prefer AIC to BIC for the replication analysis of civil war onsets[3].

[2]For theoretical and mathematical details of BMA, see Bartels 1997 and Montgomery et al. 2010

[3]Montgomery et al. 2010; I use R's BMA package customized by Montgomery et al. 2010 for the estimation. I further modify the package to allow time-dependent covariates and survival models with AIC.

Figure 18: Posterior distributions of coefficients for repeated conflict (estimator: AIC)1/3

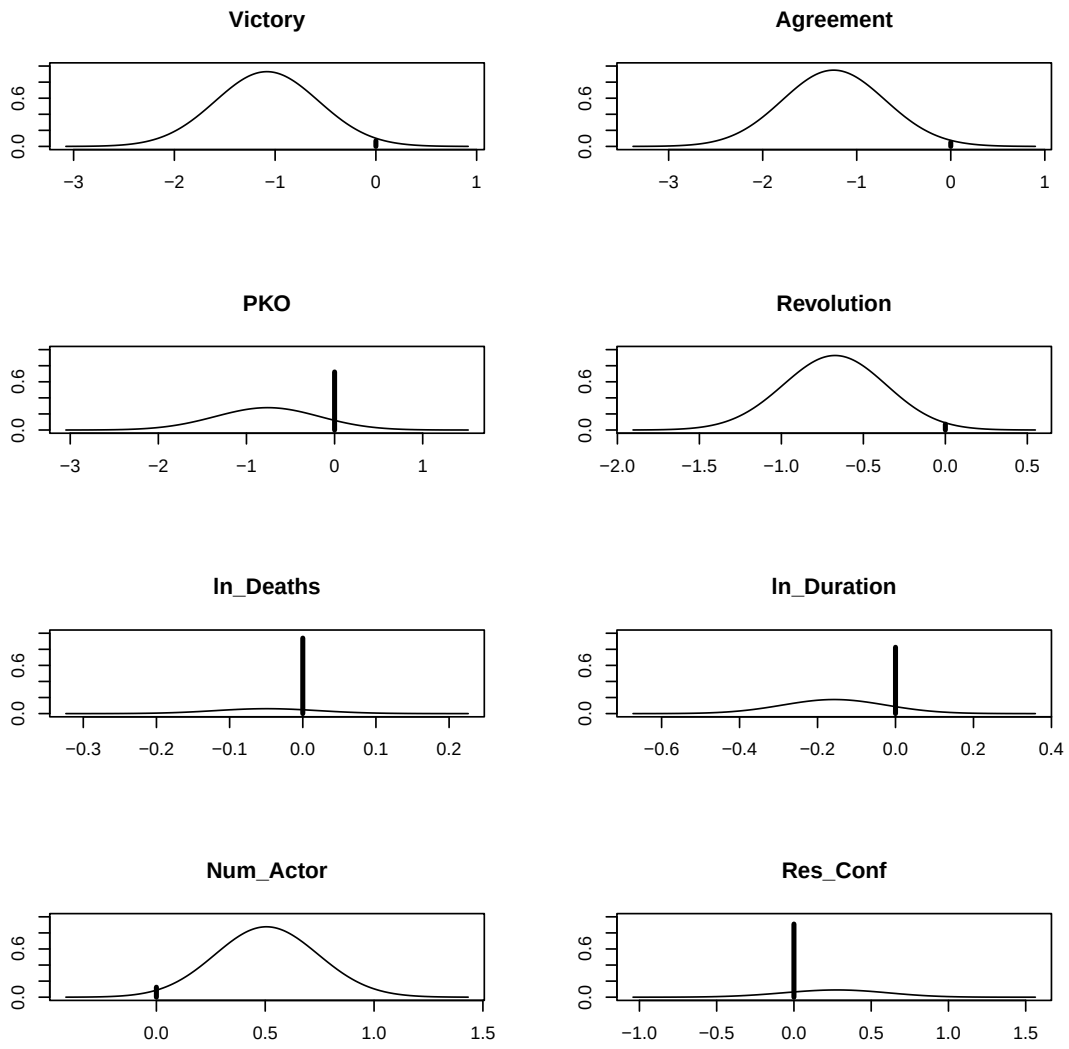


Figure 19: Posterior distributions of coefficients for repeated conflict (estimator: AIC) 2/3

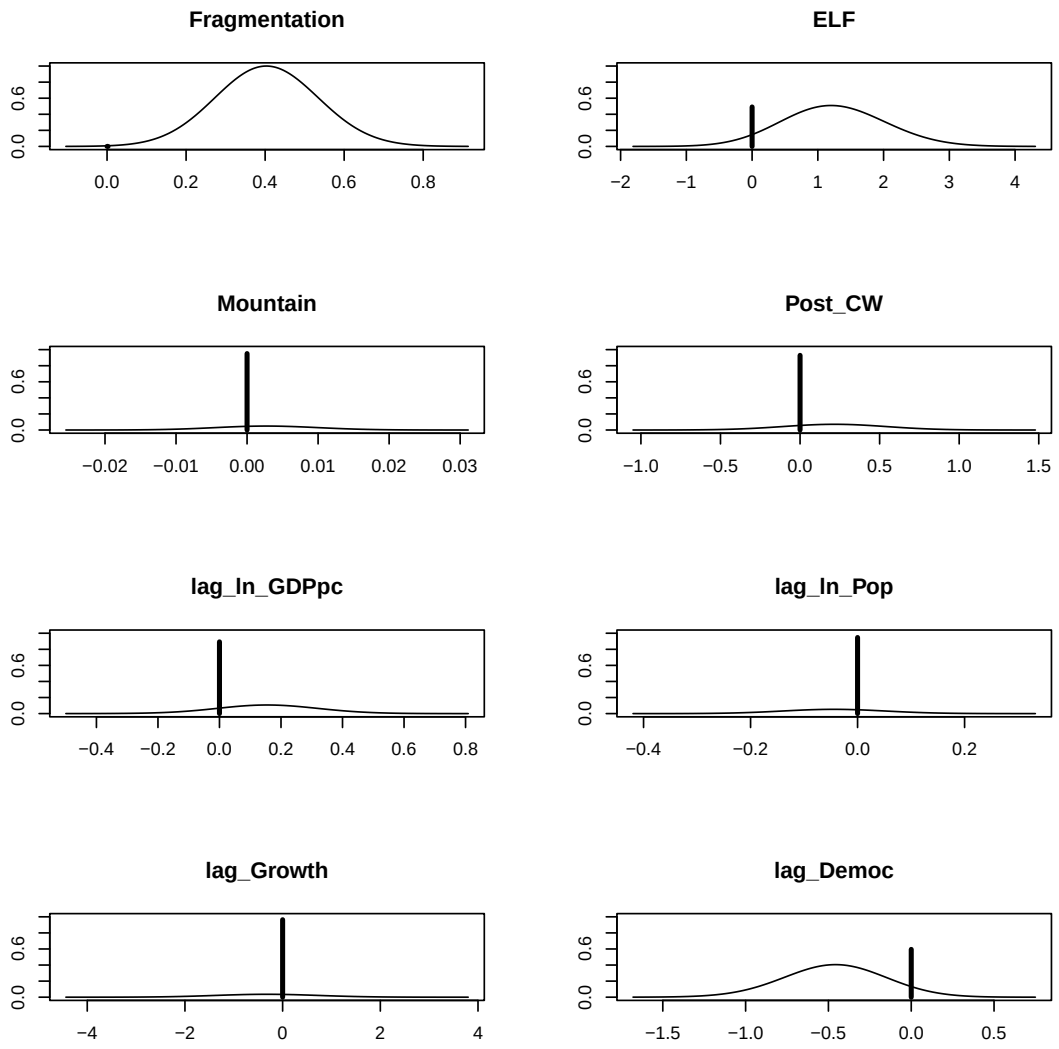


Figure 20: Posterior distributions of coefficients for repeated conflict (estimator: AIC) 3/3

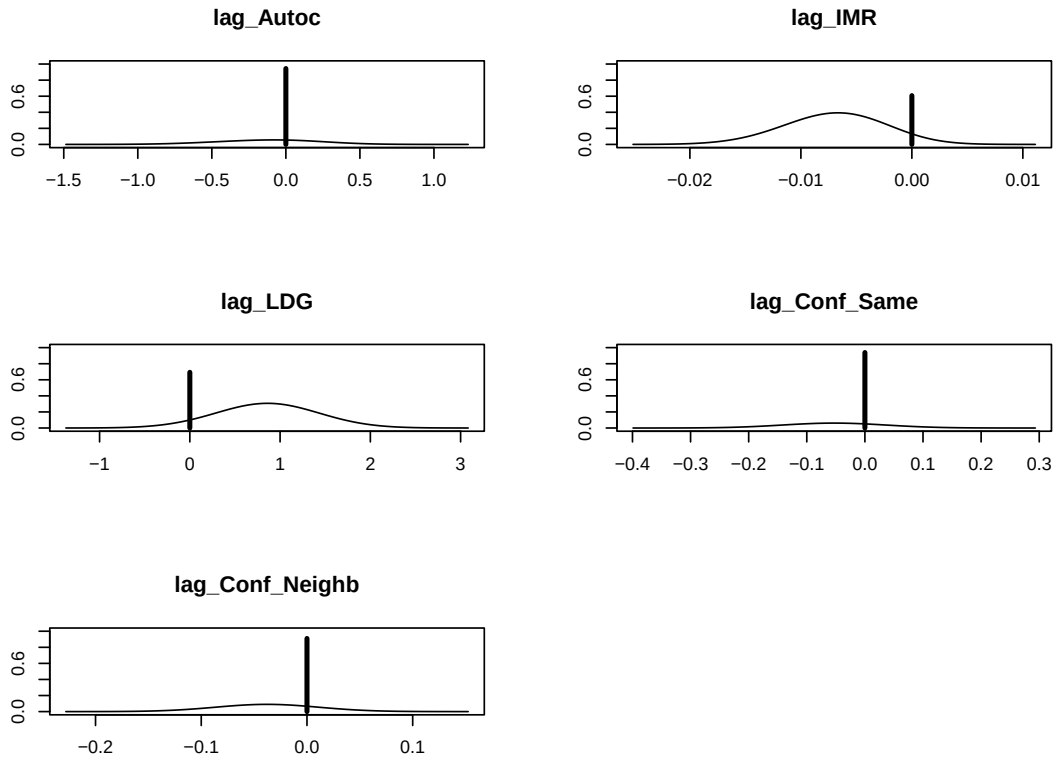


Figure 21: Posterior distributions of coefficients for recast conflict (estimator: AIC)1/3

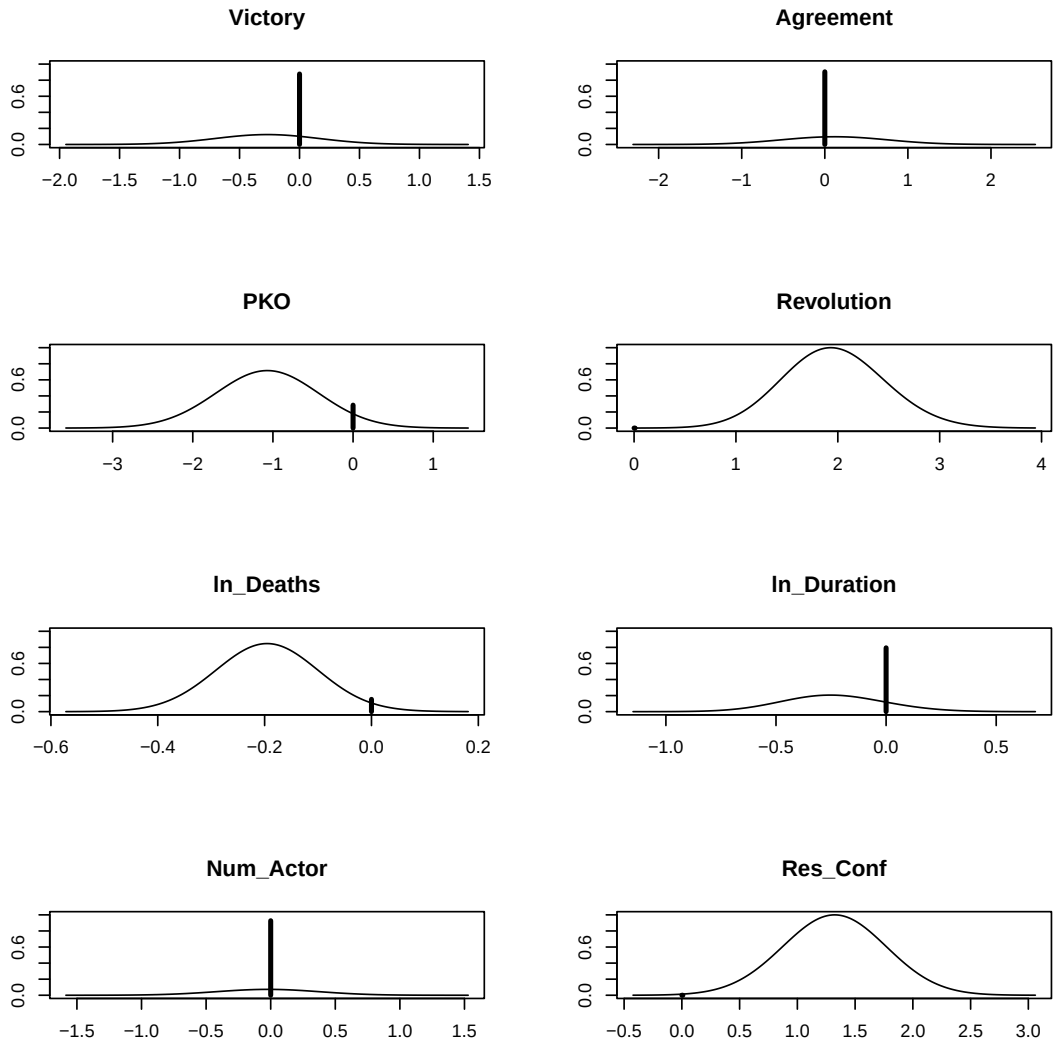


Figure 22: Posterior distributions of coefficients for recast conflict (estimator: AIC) 2/3

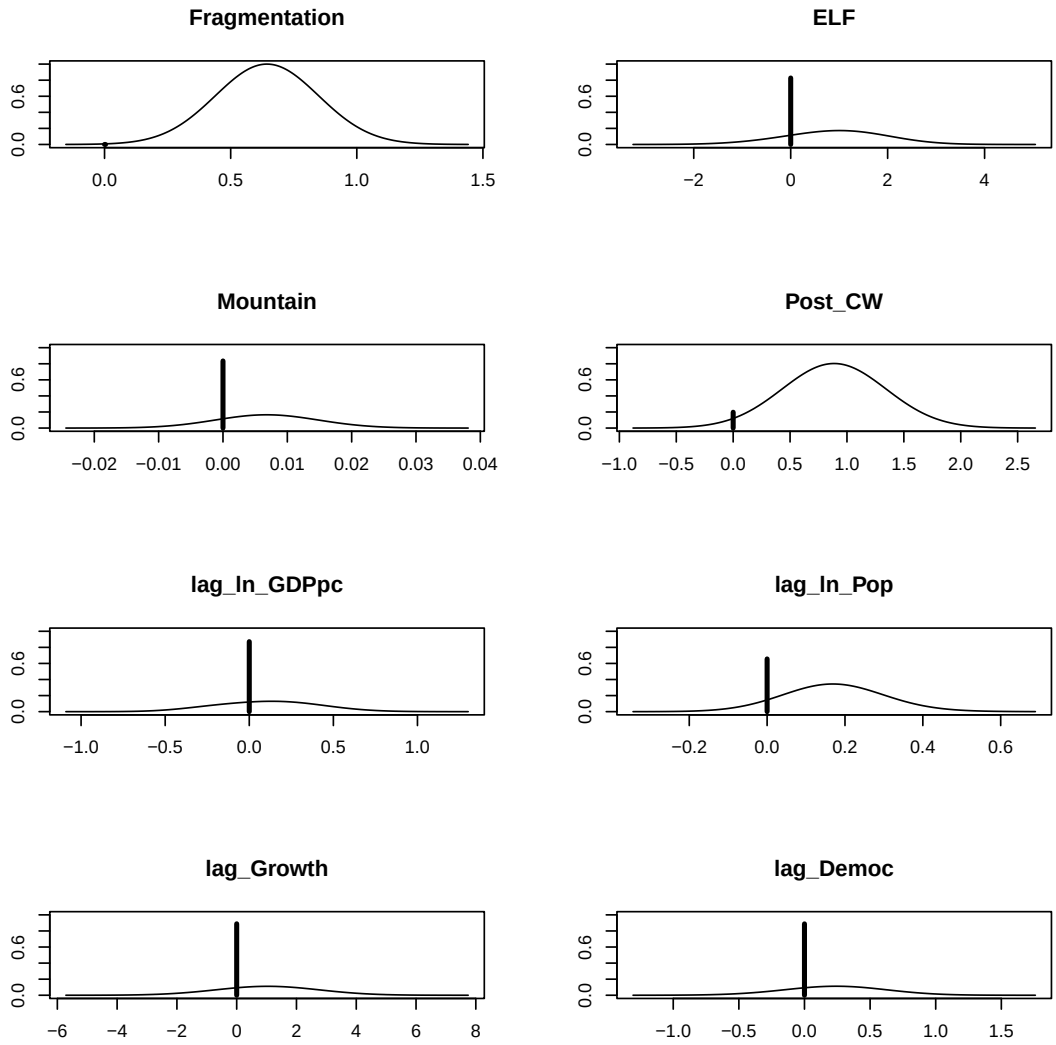


Figure 23: Posterior distributions of coefficients for recast conflict (estimator: AIC) 3/3

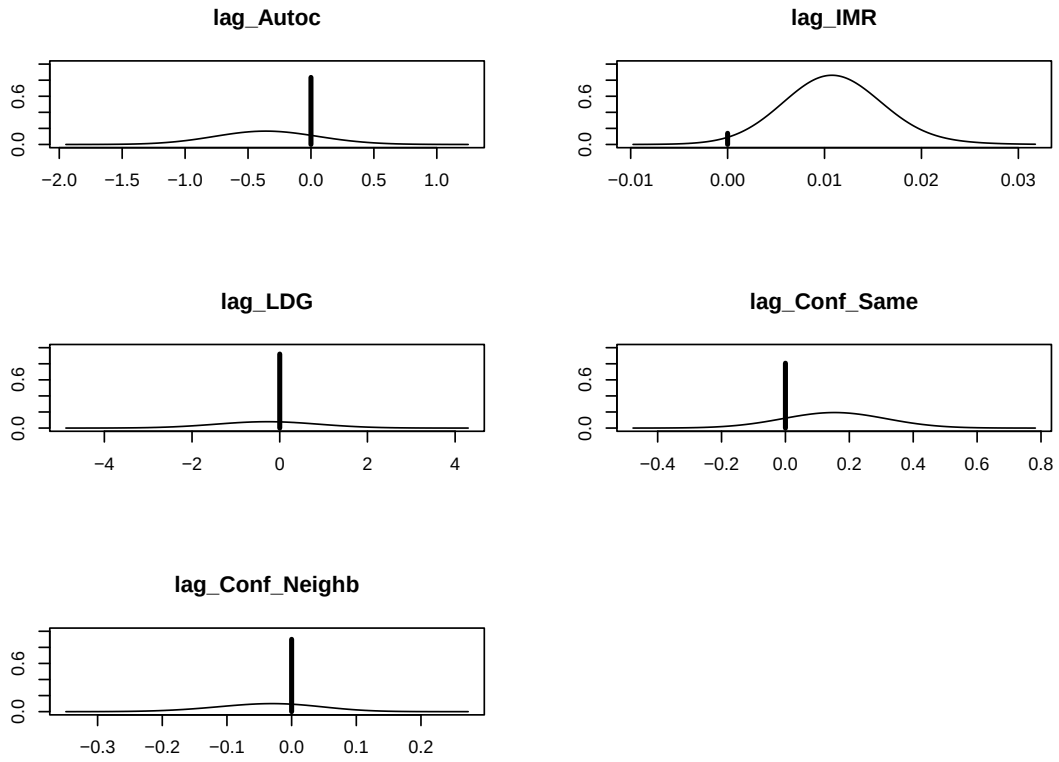


Figure 24: Posterior distributions of coefficients for repeated conflict (estimator: BIC)1/3

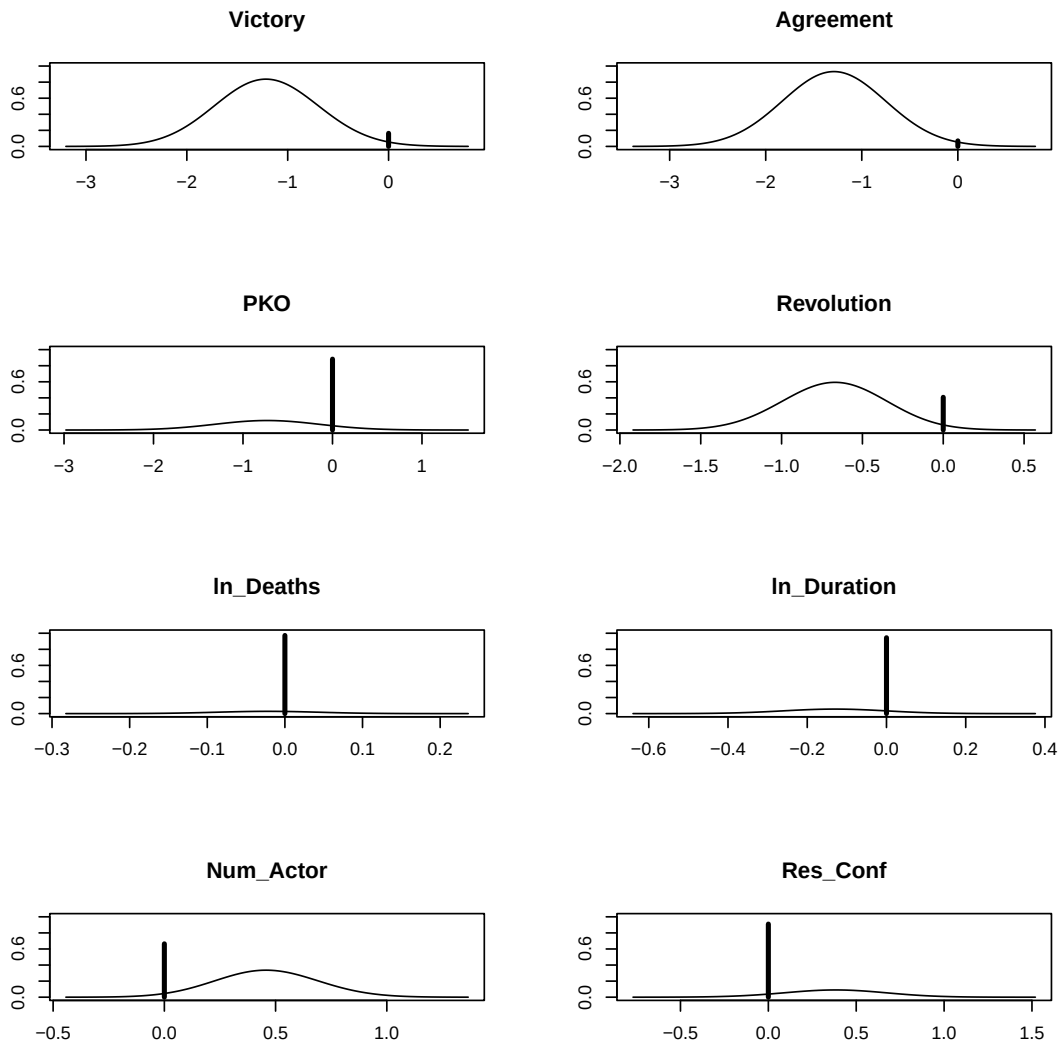


Figure 25: Posterior distributions of coefficients for repeated conflict (estimator: BIC) 2/3

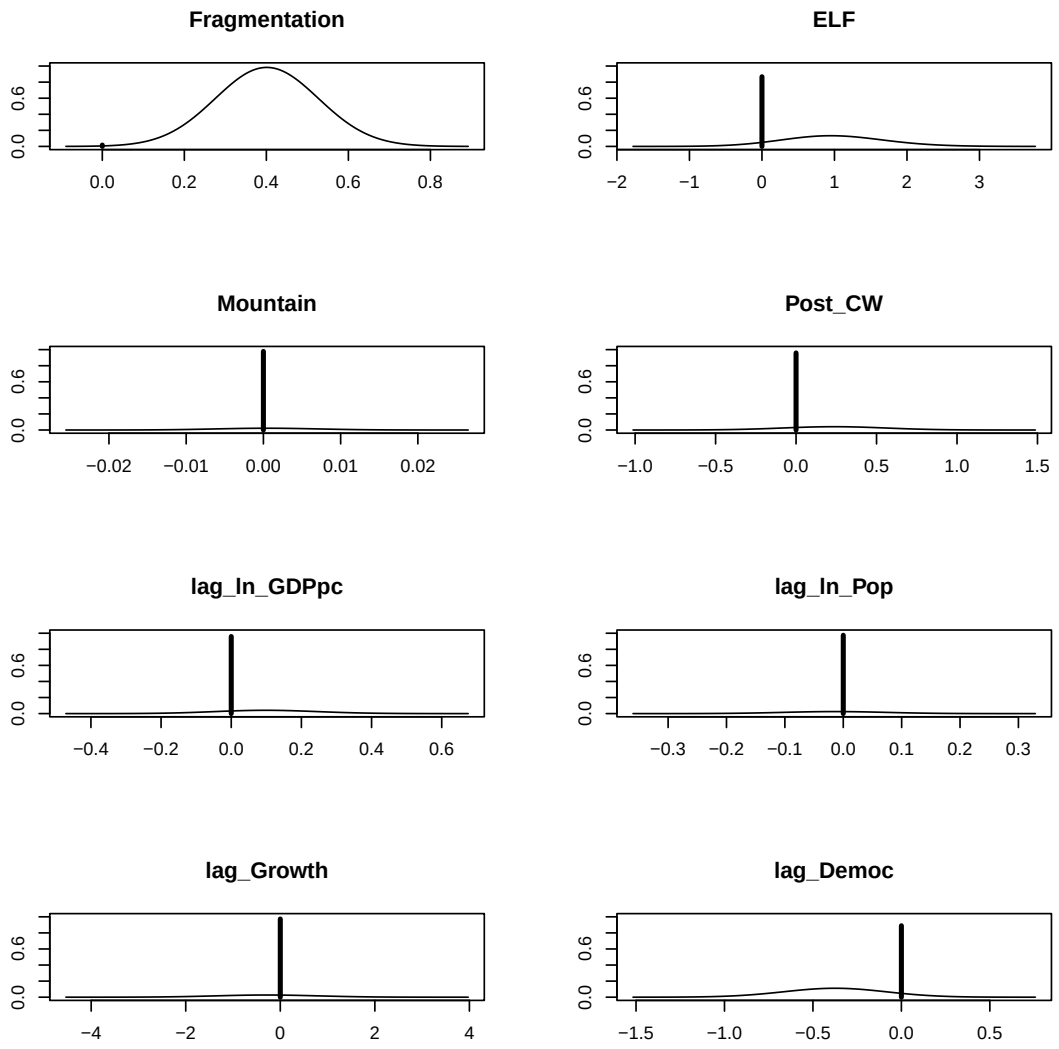


Figure 26: Posterior distributions of coefficients for repeated conflict (estimator: BIC) 3/3

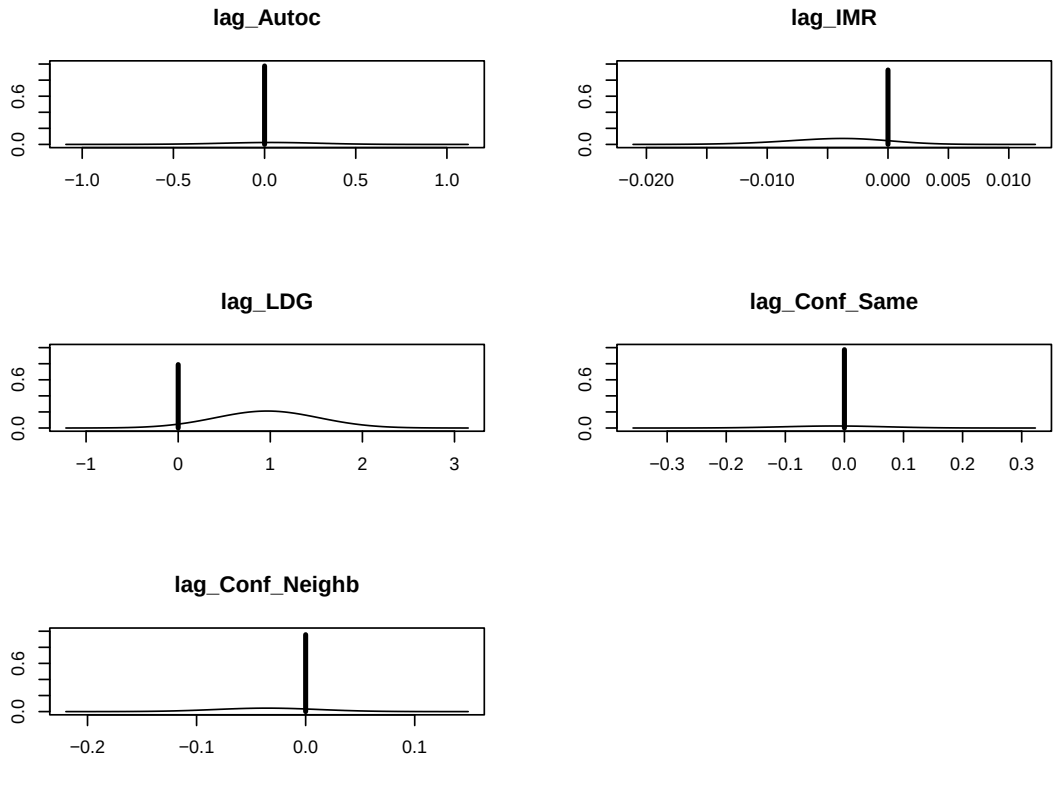


Figure 27: Posterior distributions of coefficients for recast conflict (estimator: BIC)1/3

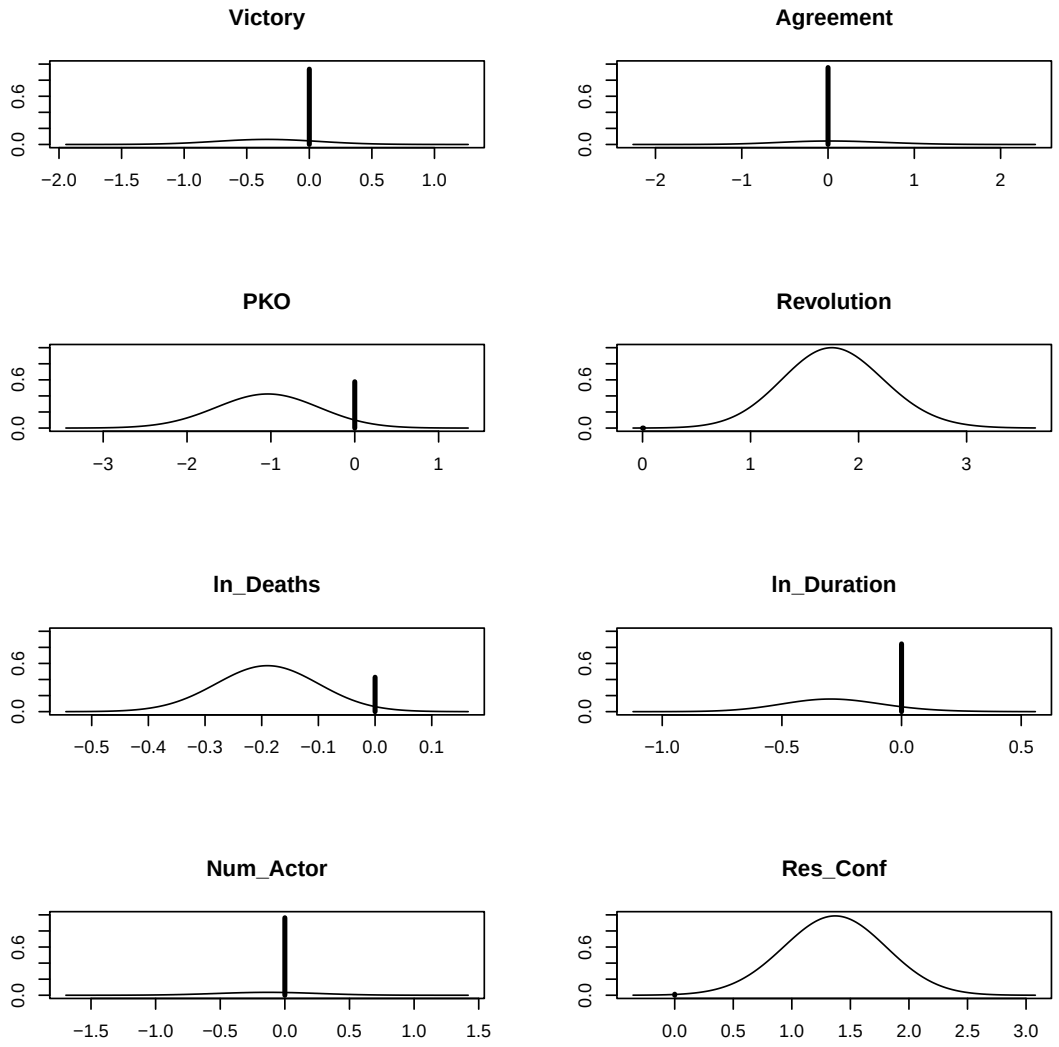


Figure 28: Posterior distributions of coefficients for recast conflict (estimator: BIC) 2/3

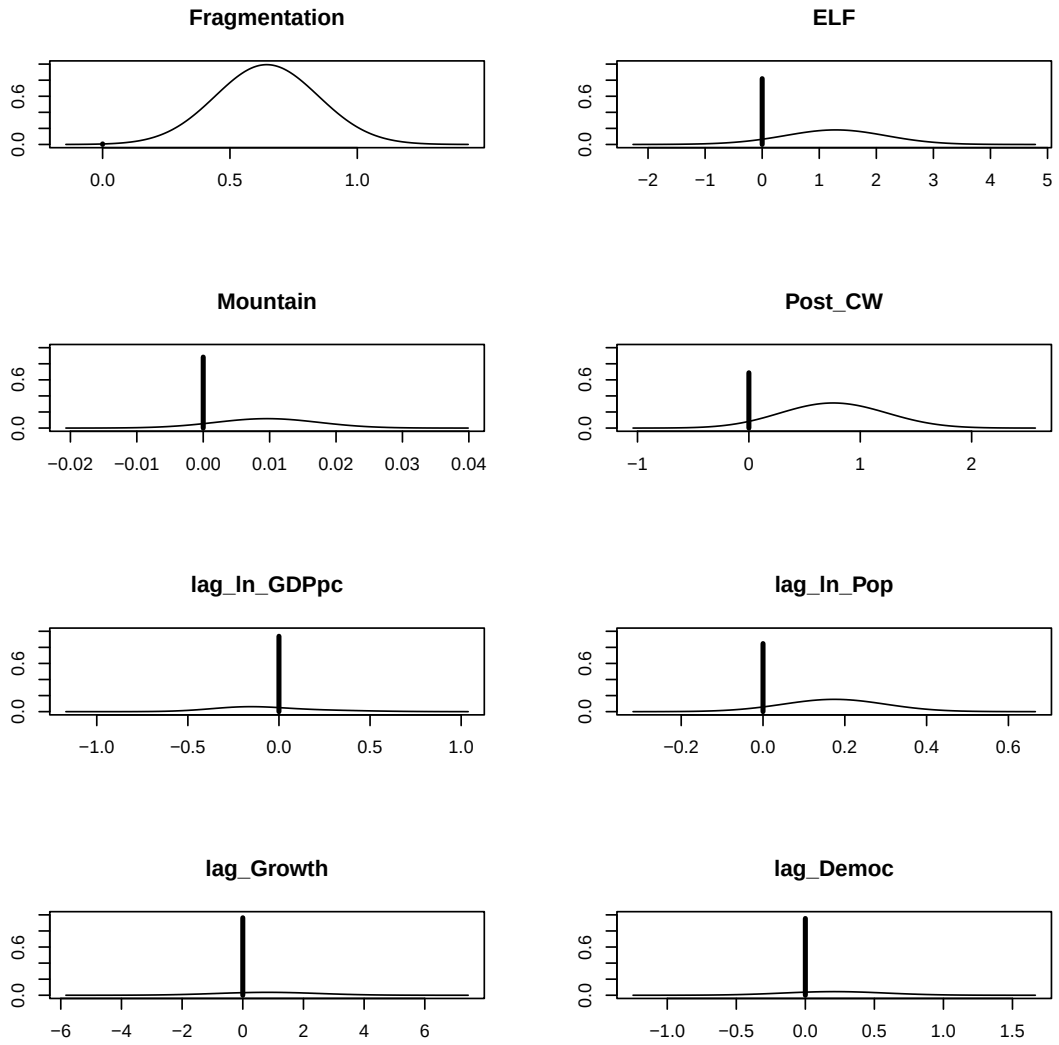
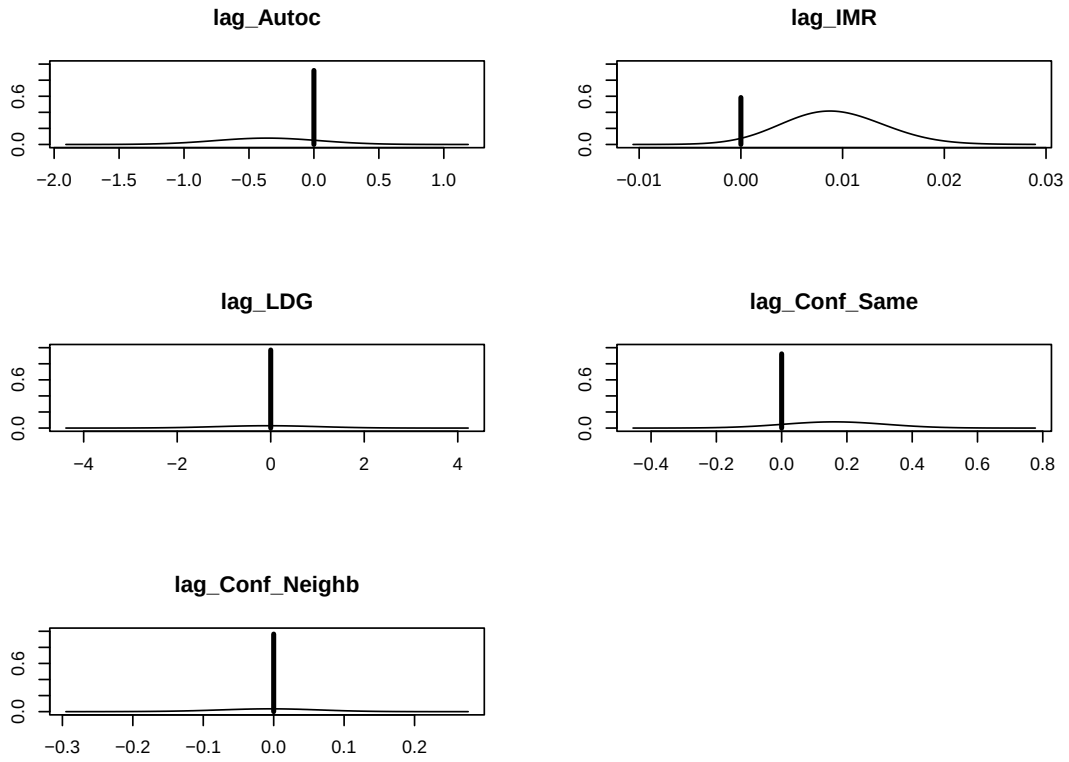



Figure 29: Posterior distributions of coefficients for recast conflict (estimator: BIC) 3/3