Every Story Has a Beginning, Middle, and an End: But Not Always in That Order

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There are three fundamental dynamics of civil conflicts: Onset, duration, and cessation. Theoretical and empirical models of war usually focus on one or at most two aspects of these three important dynamics. We argue that a better understanding of conflict needs to incorporate all three conflict dynamics as belligerents' choices to fight in the first place will depend on their expectation of fighting duration and the risk of recurrence once the fighting stops. We introduce a theoretical framework that treats onset, duration, and recurrence as interdependent processes. We also present a new duration-duration-duration estimator that treats pre-conflict duration, conflict duration, and post-conflict duration as interdependent processes thus permitting improved predictions about the onset/recurrence, duration, and cessation of conflict.

Introduction

The end of fighting cannot be equated with eternal peace. As illustrated in Figure 1, 59.1 percent of civil conflicts recur[1] and we know that a history of armed conflict makes recurrence even more likely. In the long run we can therefore observe multiple peace and armed conflict spells with varying durations [Kreutz, 2010]. Especially, empirical efforts to identify the causes of recurring and enduring conflict typically investigate the phases of peace (i.e., survival of peace until conflict breaks out) and the phases of conflict (survival of conflict until peace resumes) as if the two phases were unrelated, isolated episodes [Collier et al., 2004, Walter, 2004, Hegre and Sambanis, 2006, Quinn et al., 2007, Balch-Lindsay et al., 2008]. We challenge this literature by arguing that peace and armed conflict durations are interdependent processes that require detailed theoretical and empirical attention [Reed, 2000, Wagner, 2000, Filson and Werner, 2002, Wucherpfennig, 2011]

[1] This percentage is calculated for the period between 1946 and 2004 with the conflict data from the Uppsala Conflict Data Project.

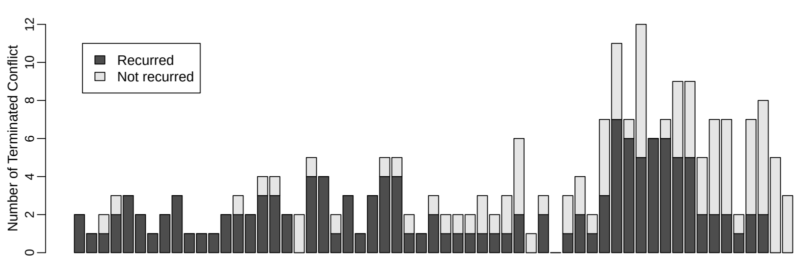

Figure 1: Conflict Recurrence Over Time, 1946–2004. This figure shows the frequency of conflict recurrence based on the UCDP data set. The height of the bars shows the number of civil conflicts terminated in a given year. The light gray bars show the number of terminated conflicts that have not recurred by the end of 2004, and the black bars show the number of terminated conflicts that have recurred by the end of 2004.

Our main contribution is to introduce the notion of "triadic duration" interdependence between the durations of pre-conflict peace, conflict, and post-conflict peace and provide an empirical estimation framework to tackle this interdependence. This perspective responds to the increasing awareness that peace and conflict periods are endogenous processes [Reed, 2000, Wucherpfennig, 2011]To a large extent scholars so far have focused on the "dyadic duration" interdependence between pre-conflict peace and fighting or post-conflict and fighting. We argue that we need to expand this perspective and allow for civil conflict actors to anticipate not only the consequences of fighting, but also anticipate the post-conflict bargaining environment.

Figure 2 illustrates why we need a "triadic duration" approach to grasp the complete data generating process of pre-conflict peace, conflict, and post-conflict peace duration. In studies that focus on the explanation of conflict onset on the pre-conflict spell is considered (panels 1-3 and panels 7-8), while information on conflict duration is not considered (panels 4-6). In addition, the peace spells (panels 1-3 and 7-8) are treated as I.I.D. and possible interdependence is not considered. Furthermore, studies that focus on conflict duration (black panels) treat them as independent of the white panels and recurrence research regards panels 7-8 independent of panels 1-5. A few studies have looked "dyadic duration" dependence, that is allowing for interdependence between *either* pre-conflict peace spells and conflict spells *or* post-conflict peace spells and conflict spells. However, each of these empirical approaches does not utilize all observed information about the conflict life-cycle.

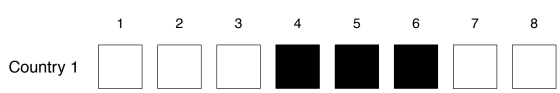

Figure 2: Stylistic Representation of Conflict Data. Panels 1-3 represent pre-conflict peace observations, panels 4-5 illustrate conflict observations, and panels 7-8 represent post-conflict peace observations.

At the conceptual level, scholars are well aware that these processes are closely interrelated. Recent formal works on organized violence have begun to look at the onset, continuation, termination, and recurrence of wars as an interrelated bargaining process [Filson and Werner, 2002, Leventoglu and Slantchev, 2007, Powell, 2004, Wagner, 2000]. The scholarly community has made a considerable progress in developing detailed datasets on various aspects of conflict dynamics over the past decades.[2] On the other hand, the analytical and predictive tools available to the empirical researchers have not yet caught up with the developments in theories and large-scale data sets.

[2] See, for example, the Correlates of War (COW) project and Uppsala Conflict Data Program (UCDP).

We propose a new empirical approach to studying phases of peace and conflict in a single, unified framework. We do so by extending the existing techniques of survival analysis. Survival analysis (also called event history analysis, hazard analysis, or duration analysis) has becomes a widely-used tool for the analyst of political events. This approach enables the researcher to model the risks of political event (e.g., conflict, democratization, leadership change) as a time dependent process. Survival analysis recognizes that the risk of event happening depends on how long the subject has *survived* previously without experiencing the event of interest. In the sense that one can interpret any binary time-series cross-sectional models as an application of survival analysis [Beck et al., 1998, Carter and Signorino, 2010], survival analysis is arguably the single most predominant mode of analysis in conflict research. Scholars of international and civil conflict have utilized the technique of survival analysis to study the duration of conflict (i.e., conflict termination) [e.g., Balch-Lindsay et al., 2008, Bennett and Stam, 1998, 1996, Bueno de Mesquita et al., 2004, Cunningham et al., 2009, Fearon, 2004, Glassmyer and Sambanis, 2008, Goemans, 2000, Krustev, 2006, Langlois and Langlois, 2009, Ramsay, 2008, Regan and Stam, 2000, Shannon et al., 2010, Slantchev, 2004, Stanley and Sawyer, 2009] and the durability of peace after and/or before conflict (i.e., conflict onset and recurrence) [e.g., Fortna, 2003, 2004, Gibler and Tir, 2010, Glassmyer and Sambanis, 2008, Grieco, 2001, Lo et al., 2008, Quackenbush and Venteicher, 2008, Senese and Quackenbush, 2003, Tir, 2003, Werner, 1999, Werner and Yuen, 2005].

Although some efforts have been made to investigate the connection between survival of peace and survival of conflict [e.g., Shannon et al., 2010, Wucherpfennig, 2011], little research has been undertaken to look at the whole life span of conflict in a coherent framework. We offer an approach to predict the onset, termination, and recurrence of violent conflict in a unified model. In so doing, we present a new statistical model that estimates consecutive duration processes jointly. We conduct empirical analyses of violent conflicts using data from the Uppsala Conflict Project over the period from 1946 to 2008.

We propose three major contributions. First, we introduce the notion of "triadic duration" interdependence to capture the strategic interdependence between pre-conflict peace, conflict, and post-conflict peace. Second, we propose a new approach to take full advantage of the information available in typical conflict data. By jointly estimating the duration of peace *and* the duration of conflict, our approach is more efficient and has a better predictive ability. This approach also facilitates stochastic simulation of the ebb and flow of conflict across the globe. Finally, we provide and apply a generic statistical model that implements our proposed framework in the context of the study of civil wars. Although the statistical model is originally developed to capture our theoretical insight about recurring violent conflict, it can readily be applied to studying other interesting political events. Potential applications of this model include democratic cycling (democratic transition and authoritarian reversal), leadership change in two-party system, among others.

The past is the present is the past: The logic of conflict and peace anticipation

At the very heart of the bargaining approach to war lies the assumption that actors are strategic. This implies that actors can anticipate the consequences of their own behavior conditional on what others might do. This anticipation means that future outcomes will condition today's behavior. For example, Schelling [1960] highlights how states condition their decision to go to war on the likely consequences of their behavior given their beliefs about the opponent they face, and vice-versa. The discipline of international relations has embraced this insight and formulated clear conditions under which bargaining breaks down and war occurs [Fearon, 1995, Powell, 1996, 2002]. In addition, the bargaining literature argues that fighting can not only be conceptualized as the consequence of bargaining, but that fighting itself can be part of the bargaining process [Wagner, 2000, Powell, 2004]. For example, Fearon [2004] demonstrates how commitment problems can lead to long periods of fighting. These insights lead to an important conclusion: The strategic logic of anticipation applies to peace and conflict bargaining. In periods of peace, actors also condition their behavior on the likely consequences of fighting, whereas in periods of fighting actors condition their behavior on the likely consequences of peace.

However, actors know that after a breakdown of peaceful bargaining, there will be a period of costly bargaining. Vice-versa, all actors know that after a period of fighting there will be a period of peaceful bargaining [Wucherpfennig, 2011]. Thus, periods of peace are conditional on periods of fighting and vice-versa. Indeed, there is a set if models that highlight the endogenous nature of these conflict situations [Wagner, 2000, Wucherpfennig, 2011]. For example, actors bargaining while fighting might anticipate disadvantageous post-conflict institutions that constrain their de-facto bargaining power. Democracies are likely to favor actors with public support, which some strong belligerents might lack.

Beyond the very strict sense of strategic behavior, there is also an element of learning that fosters the interdependence of peace and conflict spells. Actors are likely to condition their behavior on observed behavior [Slantchev, 2004, Smith and Stam, 2004]. Thus, actors constantly update their beliefs depending on what they saw in previous peace or conflict periods. Especially in countries with multiple peace and conflict spells, actors should condition their strategies on past observed behavior.

While many authors are aware of the possibility that peace bargaining impacts conflict bargaining and vice-versa [Reed, 2000, Filson and Werner, 2002], most work focuses either on the pre-conflict peace-conflict nexus or the post-conflict peace-conflict interdependence. However, we argue that this "dyadic" interdependence falls short of theorizing a "triadic" interdependence among pre-conflict peace, conflict, and post-conflict peace. So what is this "triadic interdependence"? Let us start to think about two actors in a pre-conflict period t_{-1}. We also assume that the actors can anticipate future strategic outcomes. Thus, in t_{-1} each actor anticipates the consequences of bargaining breakdown and the outcome of bargaining while fighting in t_0. In addition, each actor also anticipates the consequences of bargaining outcomes in t_0 on the post conflict bargaining period t_1 and its outcomes. This provides a rich strategic environment. Where all pre-conflict, conflict, and pre-conflict periods are conditional.

This insight not only holds when we start in the pre-conflict peace period. Let us start at time period t_0 to demonstrate this. In time period t_0 each actor has observed time period t_{-1} and is likely to condition their behavior on the observed outcome, but also on the anticipated outcome of bargaining in the post-conflict period t_1. Again, this highlights that "triadic" interdependence is likely to influence the the strategic behavior of civil conflict actors.

In fact, when we take the "triadic" interdependence seriously, there is no real temporal ordering of the interdependent bargaining periods. Even in the post-conflict period t_1 actors will condition their behavior on the previous periods and the observed behavior is also the consequence of strategic behavior of the previous periods. Thus, our theoretical perspective implies that we need to conceptualize pre-conflict, conflict, and post-conflict periods as coming from one common data-generating process. To tackle this challenge we provide a new estimator that takes into account the theoretically implied "triadic" interdependence. We test our empirical implications with a new statistical approach that jointly estimates the duration of peace and civil conflict, taking into account the dependence between the two processes. The next section introduces our statistical approach.

An empirical model of "triadic interdependence"

Let $i = 1, \ldots, n$ denote an observation unit (i.e., country) and $j = 1, \ldots, m$ denote a time unit (i.e., month). On any given day, a country is in either one of two states: peace ($y_{i,j} = 0$) or in conflict ($y_{i,j} = 1$). Figure 3 illustrates this setup graphically, with three countries and eight periods. In these hypothetical data, Country 1 experiences peace in periods 1 through 3 and 7 through 8 and conflict in periods 4 through 6. On the other hand, Country 2 only experiences peace and never experiences conflict, whereas Country 3 only experiences conflict and never experiences peace during the observed periods.

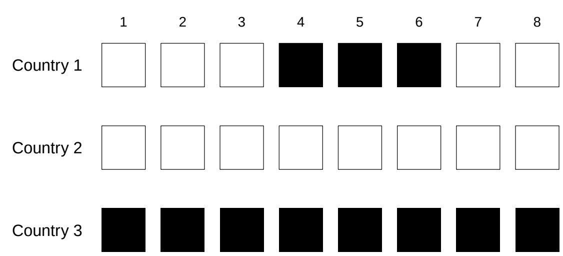

Figure 3: Stylistic Representation of Conflict Data for Three Countries. This figure illustrates the structure of typical conflict data. Panels in black show the time period where conflict is present, whereas panels in white show the time period where conflict is absent

Survival analysis (also called event history analysis or duration analysis) treats these data as a series of observations that are "at risk" of an event at each time unit. Two types of events are of our interest here: when a country is currently in peace, then the country is at risk of conflict onset; when the country is currently in conflict, then it is at risk of conflict termination. If a country in one state (peace or conflict) continues to be in the same state by the end of the time unit, we say the country "survives" the time unit. On the other hand, if a country experiences a transition from one state to the other during a time unit j, we say the country experiences a failure at j.

These at-risk observations are bound together to constitute spells. As we have two different risks in the data, two different types of spells are present. In peace spells countries are at risk of conflict onset whereas they are at risk of conflict termination in conflict spells. In our hypothetical data set, there are three peace spells as illustrated in the left-hand-side graph of Figure 4. Peace spell 1 has observed duration of 4, beginning in period 1 and ends in period 4, when a conflict breaks out in Country 1. Peace spell 2 begins in period 7 and ends in period 8 when the observation periods end. Note that peace spell 2 ends without experiencing conflict onset; therefore, we only know that peace spell 2 is at least as long as the observed length (2 periods), but we do not get to observe the full duration of peace spell

2. We treat such spells as censored spells. Peace spell 3 is also a censored spell. Similarly, the right-hand-side graph of Figure 4 illustrates conflict spells in the data. Conflict spell 1 has a duration of 4, beginning in period 4 and ending in period 7, whereas conflict spell 2 is censored in period 8.

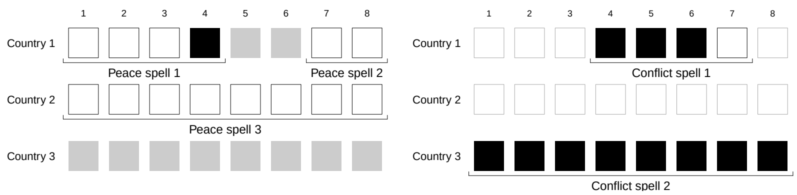

Figure 4: Peace and Conflict Spells. This figure illustrates how a separate analysis of peace and conflict duration utilizes the data. The left panel shows the information used in an analysis of peace duration, whereas the right panel shows the information used in an analysis of conflict duration.

Suppose we conduct a standard survival analysis of the duration of peace with this setting. We would be able to utilize the information from the three peace spells in our data, leaving out the remainder of the observations. As illustrated in the left-hand-side graph of Figure 4, the conflict observations shown in gray (periods 7 and 8 in Country 1 and all observations in Country 3) are simply discarded. Similarly, in a simple survival analysis of the duration of conflict would utilize the observations in conflict spells, discarding the information from the peace observations. As illustrated in the right-hand-side graph of Figure 4, such an analysis discard all the observations in gray (periods 1 through 3 and 8 in Country 1 and all the observations in Country 2). This is unfortunate, because we could potentially learn a great deal about the likelihood of peace survival from those observations that experience an enduring conflict. Likewise, observed duration of peace can also inform our inferences about conflict duration.

We thus propose a new empirical framework that allows us to utilize more information contained in the data. We do so by constructing a likelihood function that takes into account the duration of conflict (peace) spells in calculating the duration of peace (conflict) spells. In other words, our approach allows us to incorporate information from Country 3 that never experiences peace during the observation periods in estimating the duration of peace, and to incorporate information from Country 2 that never experiences conflict in estimating the duration of conflict. Moreover, our proposed model also accommodates the split-population technique that estimates the latent probability that a country is "immune" from conflict. This technique, recently introduced to political scientists [e.g., Svolik, 2008], is particularly suitable for analyzing conflict data that typically contain long periods of no conflict.

Simple Duration Model

We derive our proposed statistical model in several steps. We first introduce simple survival models for peace and conflict duration. We then introduce the joint duration model that simultaneously estimates peace and conflict duration. Finally we present our triadic duration model that jointly estimates the probability of immunity as well as peace and conflict duration. For each of the three models, we present a general model that allows time-varying covariates. That is, in all of our expositions below, the values of the covariates as well as the duration are allowed to vary by periods. We do so by evaluating the likelihood contributions from each country for each period rather than for each spell.

In the standard analysis of peace duration, the likelihood contribution from a country-day observation that experiences peace survival at time j is characterized as a conditional probability that peace survives the period j, given peace has survived up to $j-1$, or

$$\begin{aligned}\Pr(y_{i,j}=0|y_{i,j-1}=0) &= \Pr(T_i^P > t_{i,j}^P \mid T_i^P > t_{i,j-1}^P) \\ &= \frac{\Pr(T_i^P > t_{i,j}^P \ \cap \ T_i^P > t_{i,j-1}^P)}{\Pr(T_i^P > t_{i,j-1}^P)} \\ &= \frac{\Pr(T_i^P > t_{i,j}^P)}{\Pr(T_i^P > t_{i,j-1}^P)}\end{aligned}$$

where T_i^P is a random variable that represents the duration of peace for i and $t_{i,j}^P$ is the observed duration of peace for i at time j. In our hypothetical data shown in Figure 4, the values of the observed duration at periods 1 through 4 are just 1 through 4, whereas the values of the observed duration at periods 7 and 8 are 1 and 2, respectively. We use the above equation to evaluate the likelihood contributions from periods 1 through 3 and 7 through 8 in Country 1, and all periods in Country 2. [3] On the other hand, the likelihood contribution from an observation that does experience peace failure at time j (period 4 in Country 1) is given as:

[3] Practically speaking, this means that we treat periods 1 through 3 in Country 1 as if they were right-censored, even though these observations belong to a spell that is not right-censored.

$$\begin{aligned}\Pr(y_{i,j}=1|y_{i,j-1}=0) &= \Pr(T_i^P = t_{i,j}^P \mid T_i^P > t_{i,j-1}^P) \\ &= \frac{\Pr(T_i^P = t_{i,j}^P \ \cap \ T_i^P > t_{i,j-1}^P)}{\Pr(T_i^P > t_{i,j-1}^P)} \\ &= \frac{\Pr(T_i^P = t_{i,j}^P)}{\Pr(T_i^P > t_{i,j-1}^P)}.\end{aligned}$$

We then obtain the total likelihood contributions from all the observations in peace spells using the following likelihood function:

$$L^P = \prod \left[\frac{\Pr(T_i^P > t_{i,j}^P)}{\Pr(T_i^P > t_{i,j-1}^P)} \right]^{(y_{i,j}=0)(y_{i,j-1}=0)} \left[\frac{\Pr(T_i^P = t_{i,j}^P)}{\Pr(T_i^P > t_{i,j-1}^P)} \right]^{(y_{i,j}=1)(y_{i,j-1}=0)} . \tag{1}$$

This model takes into account how long peace has survived previously in calculating the likelihood of peace survival and peace failure for each period in the data. It represents a typical duration model employed in the prevalent quantitative studies of conflict onset.[4] We can also write down a typical model of conflict duration in a similar manner:

[4] It is true that there is a variation among conflict studies in terms of the observation unit (e.g., country, dyad, directed dyad), the time-unit (e.g., year, month, day), and parametric specification of the duration dependence. Nevertheless, any statistical models of conflict onset can be expressed as model (1) with some adjustment.

$$L^C = \prod \left[\frac{\Pr(T_{i,j}^c > t_{i,j}^c)}{\Pr(T_i^C > t_{i,j}^c)} \right]^{(y_{i,j}=1)(y_{i,j-1}=1)} \left[\frac{\Pr(T_{i,j}^c = t_{i,j}^c)}{\Pr(T_i^C > t_{i,j}^c)} \right]^{(y_{i,j}=0)(y_{i,j-1}=1)} , \tag{2}$$

where $T_{i,j}^c$ is a random variable that represents the duration of conflict for i and $t_{i,j}^C$ is the observed duration of conflict for i at time j.

It should be clear from these expositions that a conventional model of peace duration (1) only utilizes information from those observations where conflict is not already ongoing (i.e., $y_{i,j-1} = 0$, or Peace spells 1–3 in the left-hand-side graph of Figure 4), whereas a conventional model of conflict duration (2) focuses only on observations where conflict is already ongoing (i.e., $y_{i,j-1} = 1$, or Conflict spells 1–2 in the right-hand-side graph of Figure 4). A separate estimation of equations (1) and (2) is inefficient as each model discards information utilized in the other model. In what follows, we present a model that allows us to estimate these two processes jointly.

Joint Model of Peace and Conflict Duration

The model we present below takes into account the duration of the previous spells as well as the duration of the present spell up to the observation period. In other words, the survival of peace is formulated as a function of the survival of peace up to $j-1$ as well as the duration of the previous conflict spell. Let $T_i^{C'}$ denote a random variable representing the duration of conflict spell for i that precedes the current peace spell and $t_i^{C'}$ denote the observed duration of previous conflict spell for i. Then, the likelihood contribution from an observation that experiences peace survival at time j is characterized as a conditional probability that peace survives j, given peace has survived up to $j-1$ *and* the previous conflict has a duration $t_i^{C'}$, or

$$\begin{aligned}\Pr(y_{i,j}=0|y_{i,j-1}=0) &= \Pr\left[T_i^P > t_{i,j}^P \mid (T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})\right] \quad (3)\\ &= \frac{\Pr(T_i^P > t_{i,j}^P \,\cap\, T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}{\Pr(T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}\\ &= \frac{\Pr(T_i^P > t_{i,j}^P \,\cap\, T_i^{C'} = t_i^{C'})}{\Pr(T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}.\end{aligned}$$

Similarly, the likelihood contribution from an observation that experiences peace failure at time j is given as

$$\begin{aligned}\Pr(y_{i,j}=1|y_{i,j-1}=0) &= \Pr\left[T_i^P = t_{i,j}^P \mid (T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})\right] \quad (4)\\ &= \frac{\Pr(T_i^P = t_{i,j}^P \,\cap\, T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}{\Pr(T_i^P = t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}\\ &= \frac{\Pr(T_i^P = t_{i,j}^P \,\cap\, T_i^{C'} = t_i^{C'})}{\Pr(T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}.\end{aligned}$$

In addition, we also have the likelihood contribution from observations that experience conflict survival and conflict failure at time j, respectively, as

$$\begin{aligned}\Pr(y_{i,j}=1|y_{i,j-1}=1) &= \frac{\Pr(T_{i,j}^c > t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})}{\Pr(T_i^C > t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})}\\ \Pr(y_{i,j}=0|y_{i,j-1}=1) &= \frac{\Pr(T_{i,j}^c = t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})}{\Pr(T_i^C > t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})},\end{aligned}$$

where $T_i^{P'}$ denotes a random variable representing the duration of peace for i that precedes the current state of conflict and $t_i^{P'}$ denote the observed duration of previous phase of peace for i. We thus have the following likelihood function that calculates the total likelihood of the data:

$$\begin{aligned}L = \prod &\left[\frac{\Pr(T_i^P > t_{i,j}^P \,\cap\, T_i^{C'} = t_i^{C'})}{\Pr(T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}\right]^{(y_{i,j}=0)(y_{i,j-1}=0)} \quad (5)\\ &\left[\frac{\Pr(T_i^P = t_{i,j}^P \,\cap\, T_i^{C'} = t_i^{C'})}{\Pr(T_i^P > t_{i,j-1}^P \,\cap\, T_i^{C'} = t_i^{C'})}\right]^{(y_{i,j}=1)(y_{i,j-1}=0)}\\ &\left[\frac{\Pr(T_{i,j}^c > t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})}{\Pr(T_i^C > t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})}\right]^{(y_{i,j}=1)(y_{i,j-1}=1)}\\ &\left[\frac{\Pr(T_{i,j}^c = t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})}{\Pr(T_i^C > t_{i,j}^c \,\cap\, T_i^{P'} = t_i^{P'})}\right]^{(y_{i,j}=0)(y_{i,j-1}=1)}.\end{aligned}$$

To further characterize the likelihood function (5), we begin by specifying the univariate marginal distribution for the duration variables, T_i^P and T_i^C. Using the flexible Weibull specification, the univariate density function $f(\cdot)$, the survivor function $S(\cdot)$, and the distribution function $F(\cdot)$ are each given as a function of the scale parameter λ and the shape parameter α, as follows:

$$\begin{aligned} f(t) &= \Pr(T = t) = \lambda\alpha\,(\lambda t)^{(\alpha-1)} \exp\left(-\lambda t\right) \\ S(t) &= \Pr(T > t) = \exp\left(-\left(\lambda t\right)^{\alpha}\right) \\ F(t) &= \Pr(T \leq t) = 1 - S(t). \end{aligned} \tag{6}$$

The shape parameter determines whether the risk of "failure" event (i.e., conflict onset and conflict termination) is increasing ($\alpha > 1$), decreasing ($\alpha < 1$), or constant ($\alpha = 1$) over analysis time.

We chose the Weibull distribution because of its flexibility and simplicity. One limitation of the Weibull specification, however, is that it does not allow for non-monotonic change in hazard. As a robustness check, we also estimate log-logistic models that allow for non-monotonicity (but do not allow for a monotonic increase) in hazard. As we have two choices of parametric specifications for two types of duration processes (i.e., peace and conflict), we have four possible combinations of parametric specifications. We choose among these four models based on fit statistics after estimating all four models.

We allow the durations of peace and conflict to be conditioned on vectors of time-varying covariates, X_{ij}^P and X_{ij}^C, respectively. We do so by specifying the scale parameter governing the two durations as $\lambda_{ij}^P = \exp(-X_{ij}^P \beta^P)$ for peace duration and $\lambda_{ij}^C = \exp(-X_{ij}^C \beta^C)$ for conflict duration, where β^P and β^C are vectors of the coefficient parameters.

The next step is to characterize two types of joint distributions that appear in the likelihood function (5), namely $\Pr(T^A > t^A \cap T^B = t^B)$ and $\Pr(T^A = t^A \cap T^B = t^B)$ with $(A, B) \in \{(P, C'), (C, P')\}$. If the two random variables we have were each Normally distributed, the joint distribution of the two would simply be a bivariate Normal. However, both T^A and T^B represent duration, which we assume to be distributed Weibull or log-logistic. it is not straightforward to characterize a joint distribution whose marginal distributions are not Normal. To deal with this challenge, we utilize a copula function and derive a new joint distribution from the two duration variables. A copula is a function that binds together two or more univariate marginal distributions of known form to produce a new joint distribution [Trivedi and Zimmer, 2005]. Consider two random variables X and Y with associated univariate distribution functions $F_X(\cdot)$ and $F_Y(\cdot)$. Sklar's (1959) theorem establishes that there exists a copula

$C(\,\cdot,\ \cdot\,;\theta)$ such that a bivariate joint distribution is defined for all x and y in the extended real line as

$$F_{XY}(x,y) = \Pr(X < x \cap Y < y) = C\big(F_X(x), F_Y(y);\theta\big) \tag{7}$$

where the association parameter, θ, represents the degree of interdependence between the x and y. This result is remarkable because it shows that we can construct a new bivariate distribution based on univariate marginal distributions of known form. As long as the univariate marginal distributions are known, an appropriate choice of copula function $C(\cdot)$ in (7) enables us to represent the unknown bivariate distribution. Moreover, we can also characterize the density function and the conditional distribution functions using a copula, as follows

$$\begin{aligned}
f_{XY}(x,y) = \Pr(X = x \cap Y = y) &= \frac{\partial C\big(F_X(x), F_Y(y);\theta\big)}{\partial x\, \partial y} \qquad (8)\\
&= \frac{\partial C\big(F_X(x), F_Y(y);\theta\big)}{\partial F_X(x)\, \partial F_Y(y)} \cdot f_X(x) \cdot f_Y(y)\\
f_{X|Y}(x,y) = \Pr(X = x | Y = y) &= \frac{\Pr(X = x \cap Y = y)}{\Pr(Y = y)} = \frac{f_{XY}(x,y)}{f_Y(y)}\\
F_{X|Y}(x,y) = \Pr(X < x | Y = y) &= \int_{-\infty}^{x} f_{X|Y}(x,y)
\end{aligned}$$

where $f_X(\cdot)$ and $f_Y(\cdot)$ are the univariate density functions for X and Y.

With these functions, we can thus specify the first type of joint probability in (5) as

$$\begin{aligned}
\Pr(T^A > t^A \cap T^B = t^B) &= \Pr(T^B = t^B) - \Pr(T^A < t^A \cap T^B = t^B) \qquad (9)\\
&= \Pr(T^B = t^B) \cdot \left[1 - \frac{\Pr(T^A < t^A \cap T^B = t^B)}{\Pr(T^B = t^B)}\right]\\
&= \Pr(T^B = t^B) \cdot \left[1 - \Pr(T^A < t^A | T^B = t^B)\right]\\
&= f(t^B) \cdot \left[1 - F_{X|Y}(t^A, t^B)\right]
\end{aligned}$$

where $f(\cdot)$ is the Weibull density function as defined in (6). The second type of joint probability in (5) is obtained simply as

$$\Pr(T^A = t^A \cap T^B = t^B) = f_{XY}(t^A, t^B). \tag{10}$$

To complete the derivation, the last step is to choose a particular copula function for $C(,;\theta)$ to characterize functions in (7) and (8). There are a number of different copula functions that can be used to construct a multivariate distribution from univariate marginals [Trivedi and Zimmer, 2005], but some copulas are more flexible than others in that they can accommodate greater range of dependency between the marginals. In this study, we use the Gaussian copula, one of the most flexible copula functions that can accommodate both positive and negative dependency. It has the following form

$$C(u,v;\theta) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi(1-\theta^2)^{1/2}} \exp\left[\frac{-(s^2-2\theta st+t^2)}{2(1-\theta^2)}\right] dsdt$$

where $\Phi^{-1}()$ is the Gaussian quantile function, $-1 < \theta < 1$ is the association parameter, and $u = F_x(x)$ and $v = F_y(y)$ for random variables x and y. With the Gaussian copula, the density and the conditional functions in (8) have the following forms:

$$f_{XY}(x,y) = (1-\theta^2)^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(1-\theta^2)^{-1}(a^2+b^2-2\theta ab)\right] \exp\left[\frac{1}{2}(a^2+b^2)\right] \cdot f_X(x) \cdot f_Y(y) \tag{11}$$

$$F_{X|Y}(x,y) = \int_{-\infty}^{a} f_{XY}(x,y) = \Phi\left(\frac{a+\theta b}{\sqrt{1-\theta^2}}\right)$$

where $a = \Phi^{-1}(F_X(x))$, $b = \Phi^{-1}(F_Y(y))$, and $\Phi(\cdot)$ is the standard Normal distribution function.

The Gaussian copula has a number of desirable characteristics. First, it allows for independence as a special case ($\theta = 0$). We can thus test the existence of interdependence between the two processes by testing whether θ is different from 0. Second, the Gaussian copula is *comprehensive* in that as θ approaches the lower (upper) bound of its permissible range, the copula approaches the theoretical lower (upper) bound.[5] This is not true with other copulas that have been utilized to address selection bias in political science. For example, the estimator proposed by Sartori [2003] forces one to *assume* either one of the theoretical bounds as representing the true data generating process. The consequence of this is not only that we are unable to test the existence of interdependence but also that, depending on the assumption made about the direction of the dependency, we make completely opposite inferences about the effects of explanatory variables on outcomes. The copula function utilized in Boehmke et al. [2006] can accommodate both positive and negative dependency and allows for testing the direction of dependency, but the permissible range is limited to $\theta \in (-0.25, 0.25)$.

[5] The upper and lower theoretical bounds of a joint distribution, called Fréchet bounds, F^- and F^+, are defined as $F^-(u,v) = \max[0, u+v-1]$ and $F^+(u,v) = \min[u,v]$.

Triadic Duration Model: Joint Model with Split-population

We further extend this joint model by incorporating the split-population technique that allows us to split the observations into those that are "immune" from conflict and those that are not. This technique has been developed in medical research where researchers are interested in identifying those patients that are cured of a disease of interest (and hence not at risk of death from the said disease) and those that are still at risk. When a patient dies of the disease at a given period, researchers know with certainty that the patient has not been cured of the disease. When a patient survives a given period, however, one must consider two possibilities: the patient is cured of the disease of interest, or the patient is not cured but his/her time has not come at the period yet. Since "cure" is unobservable, a split-population model estimates the latent probability that a patient is cured or not.

We apply this technique to the study of peace and conflict by specifying the probability that a country is "immune" from conflict. In the context of conflict research, we can think of immunity as the absence of issues to fight over. According to the bargaining perspective, parties with potential issues to fight over (i.e., those that are not immune from conflict) can nevertheless avoid war if they can agree to a bargain that makes both sides better off than costly fighting. The disputants' ability to find such mutually beneficial agreements, however, is severely constrained in the presence of informational problems or commitment problems [Fearon, 1995, Powell, 2006]. We would expect that these problems generally grow over time, as there will be a greater chance that some exogenous shocks create sources of the bargaining problem. It may be the case that one party's military power grows faster than that of the other disputing party, which creates dynamic commitment problems. It may also be the case that the convergence of expectations with regard to the fighting capabilities of one another get distorted, creating informational problems. As the bargaining problem grows severer over time, the *conditional* risk of conflict onset given non-immunity should also grow over time, whereas the risk of conflict onset remains zero for immune countries (those that do not have issues to fight over in the first place). Split-population technique allows us to capture this dynamic by estimating the likelihood of immunity and the conditional risk of conflict given non-immunity.

Let $c_{i,j}$ denote a binary indicator that takes the value of 1 whenever a country is "immune" from conflict, and 0 if a country is at risk of conflict. Since we do not observe whether the right-censored country-day observations in the data are immune or not, $c_{i,j}$ is an unobservable variable. When an observation in a peace spell survives period j, the country may be either immune or non-immune from conflict. Then, the likelihood contribution from a country-day observation that experiences peace survival at time j is a combination of the likelihood that an observation is immune from conflict and the likelihood that an observation is not immune but has not experienced conflict during the period j. We can thus rewrite equation (3) as

$$\begin{aligned}\Pr(y_{i,j}=0|y_{i,j-1}=0) &= \Pr\Big[\{c_{i,j}=1\cup(c_{i,j}=0\cap T_i^P>t_{i,j}^P)\} \mid \\ &\quad \{c_{i,j}=1\cup(c_{i,j}=0\cap T_i^P>t_{i,j-1}^P\cap T_i^{C'}=t_i^{C'})\}\Big] \\ &= \frac{\Pr[c_{i,j}=1\cup(c_{i,j}=0\cap T_i^P>t_{i,j}^P\cap T_i^{C'}=t_i^{C'})]}{\Pr[c_{i,j}=1\cup(c_{i,j}=0\cap T_i^P>t_{i,j-1}^P\cap T_i^{C'}=t_i^{C'})]} \\ &= \frac{\Pr(c_{i,j}=1)+\Pr(c_{i,j}=0)\Pr[(T_i^P>t_{i,j}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]}{\Pr(c_{i,j}=1)+\Pr(c_{i,j}=0)\Pr[(T_i^P>t_{i,j-1}^P\ \cap\ T_i^{C'}=t_i^{C'})|c_{i,j}=0]},\end{aligned}$$

where $\Pr[(T_i^P>t_{i,j}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]$ is the conditional joint probability of peace survival and conflict duration given non-immunity.

On the other hand, when an observation in a peace spell experiences conflict, the country must be non-immune and $c_{i,j}=0$. To calculate the likelihood contribution from such an observation, we rewrite equation (4) as follows:

$$\begin{aligned}\Pr(y_{i,j}=1|y_{i,j-1}=0) &= \Pr\Big[c_{i,j}=0\cap T_i^P=t_{i,j}^P \mid \{c_{i,j}=1\cup(c_{i,j}=0\cap T_i^P>t_{i,j-1}^P\cap T_i^{C'}=t_i^{C'})\}\Big] \\ &= \frac{\Pr[c_{i,j}=0\cap T_i^P=t_{i,j}^P\cap T_i^{C'}=t_i^{C'}]}{\Pr[c_{i,j}=1\cup(c_{i,j}=0\cap T_i^P>t_{i,j-1}^P\cap T_i^{C'}=t_i^{C'})]} \\ &= \frac{\Pr(c_{i,j}=0)\Pr[(T_i^P=t_{i,j}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]}{\Pr(c_{i,j}=1)+\Pr(c_{i,j}=0)\Pr[(T_i^P>t_{i,j-1}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]}.\end{aligned}$$

where $\Pr[(T_i^P=t_{i,j}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]$ is the conditional joint probability density of peace duration given non-immunity.

Our proposed triadic duration model thus have the following likelihood function:

$$\begin{aligned}L=\prod &\left[\frac{\Pr(c_{i,j}=1)+\Pr(c_{i,j}=0)\Pr[(T_i^P>t_{i,j}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]}{\Pr(c_{i,j}=1)+\Pr(c_{i,j}=0)\Pr[(T_i^P>t_{i,j-1}^P\ \cap\ T_i^{C'}=t_i^{C'})|c_{i,j}=0]}\right]^{(y_{i,j}=0)(y_{i,j-1}=0)} \\ &\left[\frac{\Pr(c_{i,j}=0)\Pr[(T_i^P=t_{i,j}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]}{\Pr(c_{i,j}=1)+\Pr(c_{i,j}=0)\Pr[(T_i^P>t_{i,j-1}^P\cap T_i^{C'}=t_i^{C'})|c_{i,j}=0]}\right]^{(y_{i,j}=1)(y_{i,j-1}=0)} \\ &\left[\frac{\Pr(T_{i,j}^c>t_{i,j}^c\ \cap\ T_i^{P'}=t_i^{P'})}{\Pr(T_i^C>t_{i,j}^c\ \cap\ T_i^{P'}=t_i^{P'})}\right]^{(y_{i,j}=1)(y_{i,j-1}=1)} \\ &\left[\frac{\Pr(T_{i,j}^c=t_{i,j}^c\ \cap\ T_i^{P'}=t_i^{P'})}{\Pr(T_i^C>t_{i,j}^c\ \cap\ T_i^{P'}=t_i^{P'})}\right]^{(y_{i,j}=0)(y_{i,j-1}=1)}.\end{aligned} \tag{12}$$

We let $c_{i,j}$ be a function of covariates, $X_{i,j}^I$, and use the logit link function such that $\Pr(c_{i,j}=1)=\left(1+\exp(-X_{i,j}^I\beta^I)\right)^{-1}$. Therefore, we estimate three equations jointly: one for peace duration, one for conflict duration, and one for immunity.

The Data

We estimate the proposed model with historical data on intrastate conflict from 1946 through 2004. Our sample consists of all independent states as compiled by Gleditsch and Ward [1999].[6] During this period, 177 countries are recognized as independent states. We limit our focus on 169 countries for which reliable information is available at some point during this period.[7] This procedure generates 2,761,631 country-day observations. Each country-day observation can be either in peace (thus at risk of conflict onset) or in conflict (thus at risk of conflict termination). We determine whether or not each country-day observation is in peace or in conflict using information from the Upsala Conflict Data Program (UCDP) data sets.[8] A country-day is coded as experiencing conflict if the country experiences at least one intrastate conflict on a given day.[9] Intrastate conflicts are observed in 311,760 (11.3 %) country-days.

Based on these country-day observations, we compute the duration of peace and intrastate conflict as follows. The duration of peace at a given time point is calculated as the number of days elapsed since the closest of the following three dates: (1) the date of termination of the previous intrastate conflict; (2) the date of independence; or (3) January 1, 1946. The exact (total) duration for a given peace spell can be determined only if we get to observe an onset of civil conflict. Otherwise, we observe the duration of a peace spell up until December 31, 2004, and treat it as right-censored.[10] In our data, there are 387 unique peace spells, of which 160 spells (41.3 %) are right-censored. The remaining 227 non-censored peace spells (58.7 %) ranges from 3 days to 20,342 days (56 years) in duration. The histogram on the left side in Figure 5 shows the distribution of peace duration for the non-censored spells.

The duration of intrastate conflict at a given time point is calculated as the number of days elapsed since the closest of the following three: (1) the date of intrastate conflict onset; (2) the date of independence; or (3) January 1, 1946. In our data, there are 228 unique conflict spells, of which 8 spells are right-censored because civil conflict was ongoing in these 8 countries as of December 31, 2004. The date of conflict termination is observed for the remaining 220 non-censored spells.[11] The duration of conflict for the non-censored conflict spells ranges from 1 day to 18,264 days (50 years).[12] The histogram on the right side in Figure 5 shows the distribution of conflict duration for the non-censored spells.

[6] We used version 5.0 of the list of independent states, available online at `http://privatewww.essex.ac.uk/~ksg/statelist.html` (accessed on May 1, 2013).

[7] In other words, we drop 8 countries for which information on country-specific characteristics is unavailable for any period between 1946 and 2004. The excluded countries are: Barbados, Luxemburg, Iceland, Zanzibar, Maldives, Tibet, Brunei, and East Timor.

[8] We used version 4 of the UCDP/PRIO Armed Conflict Dataset as well as the UCDP Conflict Termination Dataset v.2000-1, available online at `http://www.pcr.uu.se/research/UCDP/` (accessed on May 1, 2013).

[9] A country can experience more than one intrastate conflict at a given time. Rather than duplicating observations for those country-days with multiple ongoing conflicts, we treat them as one observation for each.

[10] In fact, the UCDP data sets provide information up until December 31, 2008. We nevertheless choose 2004 as the censoring point for two reasons. First, we use the observations from 2005 through 2008 as "out-of-sample" data with which to assess the predictive abilities of our models. Second, reliable information on many covariates is available only up to 2004.

[11] As there are 220 conflict spells with termination, there are 220 post-conflict peace spells for which we can observe conflict *recurrence*. Conflict recurred by the end of 2004 in 130 (59.1 %) post-conflict spells.

[12] The longest conflict spell is observed for Israel (1949–1999).

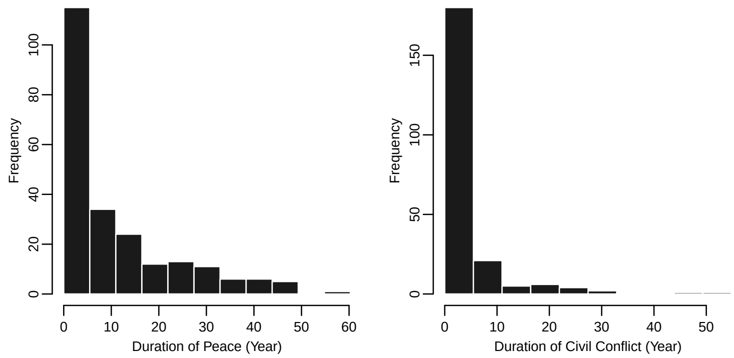

Figure 5: Duration of Peace and Civil Conflict, 1946–2004. The histogram to the left shows the duration of peace (in years) for the non-censored peace spells ($n = 227$). The histogram to the right shows the duration of civil conflict (in years) for the non-censored conflict spells ($n = 220$).

We test the empirical implications of our theoretical argument with a set of variables measuring the characteristics of peace and conflict spells. `Multilateral conflict` takes the value of 1 for conflict spells where the government fights with more than one rebel groups at any point during the course of observation, and 0 otherwise. Specifically, this variable is coded 1 when (1) the government fights more than one intrastate conflicts in a given spell, or (2) the government fights more than one rebel groups in at least one intrastate conflict at any given time in a given spell. We rely on information from the UCDP Armed Conflict Dataset (the `SideB` variable) in coding this variable. `Conflict over territory` takes the value of 1 for conflict spells where the incompatible positions between the government and rebel only concerns territory, and 0 otherwise. Similarly, `Conflict over government` takes the value of 1 for conflict spells where the parties fight over government, and 0 otherwise.[13] We use the `Incompatibility` variable from the UCDP data set to code these variables.

[13] Conflict spells concerning both territory and government are therefore the baseline. In other words, when the parties fight over both of these two issues, `Conflict over territory` and `Conflict over government` both take the value of 0.

To differentiate peace spells with the characteristics of the preceding conflict, we prepare the following variables. `Peace following a conflict` takes the value of 1 for post-conflict peace spells, and 0 for peace spells that begin either on January 1, 1946 or the date of independence. `Peace following a multilateral conflict` takes the value of 1 for post-conflict peace spells where the value of `Multilateral conflict` for the preceding conflict is 1, and 0 for non post-conflict peace spells and post-conflict peace spells that follow a bilateral conflict. `Peace following conflict over territory` and `Peace following conflict over government` are coded in a similar manner. Furthermore, we use information from the UCDP Conflict Termination Dataset to code how the preceding conflict is terminated. `Peace following government victory` takes the value of 1 for post-conflict peace spells where the preceding conflict ends in government victory, and 0 for non post-conflict peace spells and post-conflict peace spells where the preceding conflict does not end in government victory. `Peace following rebel victory` takes the value of 1 for post-conflict peace spells where the preceding conflict ends in rebel victory, and 0 for non post-conflict peace spells and post-conflict peace spells where the preceding conflict does not end in rebel victory. Finally, `Peace following peace/ceasefire agreements` takes the value of 1 for post-conflict peace spells where the disputing parties ends the preceding conflict with either a peace agreement or a ceasefire agreement.

We also control for a number of structural characteristics of a country. These variables are taken from Fearon and Laitin [2003] and Bleaney and Dimico [2011]. We impute the missing values of the structural variables using the semiparametric imputation technique proposed by Hoff [2007].

Empirical Results

Table 1 shows the estimated coefficients from our proposed triadic duration model of peace and conflict duration with Weibull parametrization for both processes. As we noted previously, we chose the parametric specification based on fit statistics. Specifically, we estimated four different models that employ different combinations of parameterization: Weibull (peace)–Weibull (conflict), Weibull (peace)–Log-logistic (conflict), Log-logistic (peace)–Weibull (conflict), and Log-logistic (peace)–Log-logistic (conflict). These models generate Akaike Information Criterion (AIC) scores of 7668, 7696, 7669, and 7693, respectively. We thus chose Weibull–Weibull specification as it generates the lowest AIC score. As we have three equations, there are three sets of coefficients. Coefficients for the peace and conflict duration (first and second columns) are represented in the accelerated failure time metric; positive estimates are thus associated with longer duration. Variables with positive estimates in the "Immunity" equation (third column) are associated with higher likelihood that the country is immune from conflict. Finally, estimates for the auxiliary parameters, α and θ, are shown at the bottom of the table.[14]

We can see that the estimated $\log(\alpha)$ for peace spells is positive, generating $\alpha > 1$. This result implies that the conditional risk of conflict onset given "non-immunity" is increasing over time, controlling for the covariates and the interdependence of conflict and peace duration. This is consistent with the theoretical expectations from the bargaining perspective. As discussed above, we expect that the risk of bargaining breakdown for parties with potential issues to fight over (i.e., those that are not immune from conflict) should grow larger over time. The estimated $\log(\alpha)$ for conflict spells is negative,

[14] Note that α and θ are re-parameterized as $\log(\alpha)$ and $\tanh^{-1}(\theta)$, respectively. This is necessary because the duration dependence α can only take positive values, and the correlation θ is only defined between -1 and 1.

	Peace Duration	Conflict Duration	Immunity
Characteristics of Peace			
Peace following a conflict	−3.39		
	(0.39)		
Peace following a multilateral conflict	−0.13		
	(0.21)		
Peace following government victory	1.15		
	(0.20)		
Peace following rebel victory	0.36		
	(0.26)		
Peace following conflict over territory	0.80		
	(0.28)		
Peace following conflict over government	1.30		
	(0.31)		
Peace following peace/ceasefire agreements	0.59		
	(0.20)		
Characteristics of Conflict			
Multilateral conflict		0.85	
		(0.41)	
Conflict over territory		−1.22	
		(0.63)	
Conflict over government		−1.61	
		(0.63)	
Structural Factors			
Per capita GDP (logged)	0.43	−0.16	
	(0.09)	(0.15)	
Oil	−0.68	−0.27	
	(0.17)	(0.32)	
There exist 1+ excluded groups	−0.25	0.63	
	(0.20)	(0.34)	
Ethnic Fractionalization	0.61	−0.18	−3.41
	(0.29)	(0.51)	(1.09)
Cold War	0.22	0.59	−1.20
	(0.14)	(0.26)	(0.57)
Anocracy			−7.69
			(2.83)
Constant	6.87	8.65	1.07
	(0.75)	(1.33)	(0.57)
$\log(\alpha)$ (duration dependence)	0.21	−0.59	
	(0.06)	(0.05)	
$\tanh^{-1}(\theta)$ (correlation)	0.10		
	(0.01)		
Number of spells (time-constant)	387	228	
Number of observations (time-varying)	6944	1123	

Table 1: Triadic Duration Model of Peace and Conflict, 1946–2004

generating $\alpha < 1$. This suggests that the risk of conflict termination is decreasing over time, other things being equal. Finally, the estimated correlation parameter $\tanh^{-1}(\theta)$ is positive, generating $\theta = 0.1$. This suggests that peace duration and conflict duration are positively correlated, conditional on the covariates and our model specifications.

To illustrate the relevance of our triadic approach, Table 2 compares the estimation results from our triadic model with a simple model of conflict and peace duration.[15] The first column reports the results from two simple duration models, one for peace spells and the other for conflict spells.[16] These results correspond to the results typically reported in conflict research that assumes as if the two processes were unrelated. The second column reproduces the same results reported in Table 1. Figures 7 and 8 plot these coefficients along with the estimated confidence intervals to illustrate the differences in the estimates. We can assess the relative performance of these models by comparing Akaike Information Criterion (AIC) scores from each model, as the first model is nested in the second. We can see that our triadic duration model fits the data better than either of the other two models, yielding the lowest AIC score of all three.

One of the striking differences between the estimates from these different models is that the values of the estimated duration dependence for peace spells differ sharply by models. The estimate is

[15] Coefficients for the intercept and some of the structural variables are omitted for brevity.

[16] We obtained the results for the first column by estimating the two equations simultaneously while assuming there is no correlation between the two equations. Such "joint but independent" estimation is mathematically equivalent to estimating two separate models for peace and conflict duration.

negative in the simple duration model, suggesting that, without accounting for the interdependence nor the unobserved immunity, the risk of conflict onset is decreasing over time. On the other hand, the estimate is positive in our triadic duration model.

Table 2: Results from Simple Duration Models and the Triadic Model

	Simple Duration	Triadic Duration
Peace Equation		
Peace following a conflict	−2.13	−3.39
	(0.52)	(0.39)
Peace following a multilateral conflict	−0.12	−0.13
	(0.33)	(0.21)
Peace following government victory	0.83	1.15
	(0.27)	(0.20)
Peace following rebel victory	−0.13	0.36
	(0.36)	(0.26)
Peace following conflict over territory	0.73	0.80
	(0.46)	(0.28)
Peace following conflict over government	1.29	1.30
	(0.48)	(0.31)
Peace following peace/ceasefire agreements	0.29	0.59
	(0.28)	(0.20)
$\log(\alpha)$ (duration dependence)	−0.18	0.21
	(0.06)	(0.06)
Conflict Equation		
Multilateral conflict	0.82	0.85
	(0.41)	(0.41)
Conflict over territory	−1.07	−1.22
	(0.62)	(0.63)
Conflict over government	−1.44	−1.61
	(0.62)	(0.63)
$\log(\alpha)$ (duration dependence)	−0.64	−0.59
	(0.05)	(0.05)
Immunity Equation		
Ethnic Fractionalization		−3.41
		(1.09)
Anocracy		−7.69
		(2.83)
Cold War		−1.20
		(0.57)
$\tanh^{-1}(\theta)$ (correlation)		0.10
		(0.01)
Log-likelihood	−3898	−3805
AIC	7843	7668

These results make sense in light of the bargaining perspective. As discussed above, the bargaining perspective suggests that the *conditional* risk of conflict onset *given non immunity* should be increasing over time, as there will be greater chances of bargaining breakdown over time as long as the issues to fight over are present. Our triadic duration model captures this dynamic, whereas the other two models fail to do so. The simple duration model generates negative duration dependence, implying that the risk of conflict onset appears to be decreasing over time. This is driven by the fact that many of the countries that are immune from conflict (i.e., those that do not have parties with issues to fight over) experience long duration of peace and thus the ratio of immune countries to all the surviving countries must be growing over time. Then, if we fail to account for the unobservable immunity, it may *appear* to be the case that the risk of conflict onset is declining.

To illustrate the better fit of our proposed model, we calculate the expected duration for uncensored peace and conflict spells according to the triadic duration model and the simple duration model. Figure 6 displays the estimated probability densities of expected duration according to the simple duration model (dashed curve) and our triadic duration model (solid curve) against a histogram of the

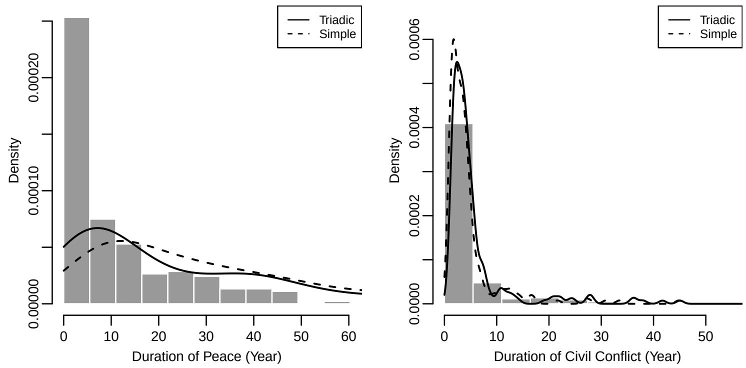

Figure 6: Observed and Predicted Distribution of Uncensored Duration. The histograms show the empirical (i.e., observed) distribution of peace (left) and conflict (right) duration for uncensored spells. In each graph, solid curves in black show the estimated density of duration according to our joint model, whereas dashed curves in red show the estimated density of duration according to simple model duration models.

observed uncensored duration of peace (left) and conflict (right). The left-hand-side graph clearly shows that the triadic duration model predicts a distribution of duration that is much closer to the actual distribution of the uncensored duration of peace, although the two models hardly differ in performance for the conflict spells. This suggests that the proposed model provides a much better fit to the data on peace duration than do models typically employed in the literature.

Table 3: Out-of-Sample Predictions for Peace and Conflict Spells

Country	**Start**	**End**	**Observed Duration**	**Predicted Duration**		**Absolute Error**	
Peace Spells				Triadic	Simple	Triadic	Simple
Turkey	1993-01-01	2005-06-17	4549	5064	13504	515	8955
Mali	1995-01-01	2007-08-31	4624	5064	8621	440	3997
Azerbaijan	1995-03-18	2005-10-09	3857	5970	17406	2113	13549
Niger	1997-11-30	2007-04-30	3437	4352	6358	915	2921
Peru	2000-01-01	2007-11-14	2873	4506	9317	1633	6444
Israel	2000-01-01	2006-07-13	2384	2448	9812	64	7428
Congo (Dem. Rep.)	2002-01-01	2006-11-28	1791	2492	3203	701	1412
Central African Republic	2003-01-01	2006-11-28	1426	5022	7247	3596	5821
Chad	2003-01-01	2005-12-18	1081	1898	3147	817	2066
Myanmar	2004-01-01	2005-01-16	380	916	2307	536	1927
Sri Lanka	2004-01-01	2005-12-02	700	2813	6339	2113	5639
Georgia	2004-08-20	2008-08-08	1448	1666	4592	218	3144
Median Absolute Error						759	4818
Conflict Spells							
Burundi	1994-10-18	2006-09-08	4343	654	474	3689	3869
Nepal	1996-08-23	2006-11-22	3743	976	711	2767	3032
Indonesia	1999-06-19	2005-10-13	2308	909	667	1399	1641
Russia	1999-07-18	2007-10-08	3004	1928	1346	1076	1658
Ivory Coast	2002-09-20	2005-01-01	834	480	367	354	467
Haiti	2004-02-09	2005-01-01	327	501	364	174	37
Median Absolute Error						1238	1650

We further demonstrate the usefulness of our approach by calculating the predicted duration for the out-of-sample periods. Specifically, we calculate the expected duration for all the spells that are censored on December 31, 2004 and subsequently uncensored by December 31, 2008. In our data, there are 12 peace spells and 6 conflict spells that fit this description. For each of these 12 peace spells, we calculate the predicted duration until the onset of a next conflict according to our triadic duration model and the simple duration model.[17] Similarly, for each of these 6 conflict spells we calculate the predicted duration until conflict termination.

[17] The predicted duration until "failure" is obtained by calculating the expected value of a duration variable. By definition, the expected value of a random variable is obtained by multiplying the t by the density function $f(t)$ and integrating, such that $E(T) = \int_0^\infty t f(t) dt = \int_0^\infty S(t) dt$. We used the values of the covariates for December 31, 2004 to calculate the values of $S(t)$ from each model.

Table 3 summarizes the results. The third column shows the observed duration until conflict onset or termination in days. The fourth and fifth columns show the predicted duration according to the triadic and simple duration models. The last two columns show the absolute difference between the observed and predicted values of spell duration. We can see that our triadic duration model performs remarkably better compared with the simple duration model. Indeed, for the peace spells, estimates from our preferred approach provide a median prediction error that is 6 times smaller (smaller by 11 years) compared with the simple duration model. The reduction in error is less pronounced for the conflict spells, but the error is smaller by more than 1 year for our approach.

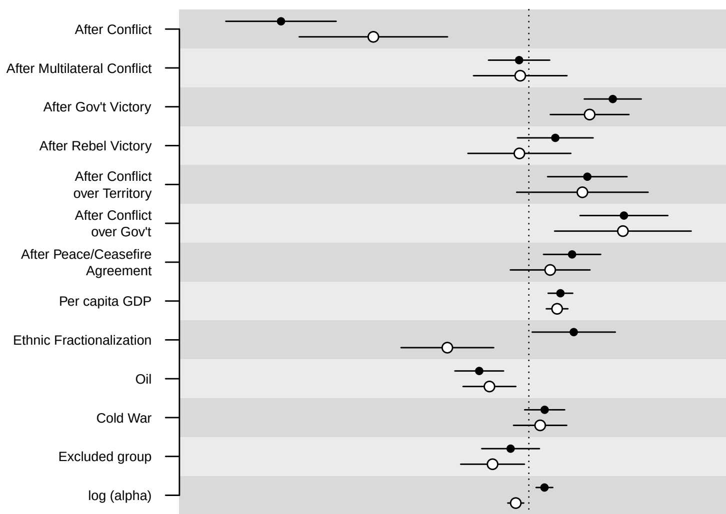

Figure 7: Comparing Coefficients: Peace Spells. Circles show the point estimates and horizontal line segments associates with circles show the 95% confidence intervals. Solid circles show the results from our triadic model of peace and conflict duration, whereas hollow circles are from the separate model of peace duration.

Conclusion

This might be the end to this article, but it is hopefully the beginning of further research to theoretically and empirically embrace the notion that we need to treat pre-conflict peace duration, conflict duration, and post-conflict peace duration as interdependent processes. Our main argument is that we should not only focus on the dependence between *either* pre-conflict peace duration and conflict duration *or* pre-conflict peace duration and conflict duration, but that we need to deal with "triadic duration" interdependence in the context of civil conflicts. This perspective is motivated by the assumption that actors are strategic and can anticipate not only the outcomes of a conflict bargaining phase, but also consider the anticipated outcomes of a potential post-conflict bargaining process.

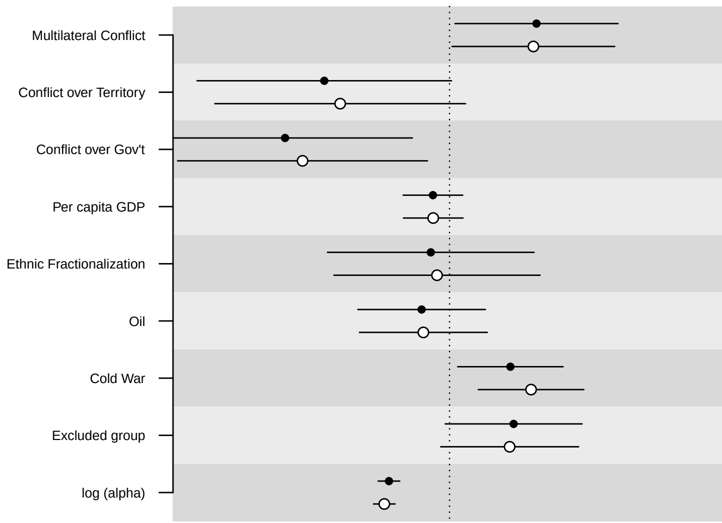

Figure 8: Comparing Coefficients: Conflict Spells. Circles show the point estimates and horizontal line segments associates with circles show the 95% confidence intervals. Solid circles show the results from our triadic model of peace and conflict duration, whereas hollow circles are from the separate model of conflict duration.

Herein, we introduced an estimation approach that captures important elements of this “triadic duration” interdependence. Our empirical results demonstrate that a model that allows for interdependence provides improved out-of-sample predictions. The improved prediction performance is likely to be driven by more precise estimates that are provided by our approach.

Our proposed model not only fits the data better but also reveals some interesting conflict dynamics that a simple duration model fails to capture. Specifically, our model implies that the conditional risk of conflict onset given non-immunity is growing over time, consistent with the bargaining perspective. This dynamic is masked in a simple duration model that conflates the “immune” disputants that experience long peace because there is no issue to fight over and those “non-immune” ones that experience long peace because they manage to maintain peace in the presence of such issues.

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