Every Story Has a Beginning, Middle, and an End (But Not Always in That Order): Predicting Duration Dynamics in a Unified Framework

Daina Chiba, Nils W. Metternich and Michael D. Ward

Political Science Research and Methods / Volume 3 / Issue 03 / September 2015, pp 515 - 541
DOI: 10.1017/psrm.2014.46, Published online: 11 March 2015

Political Science Research and Methods Vol 3, No. 3, 515–541 September 2015

doi:10.1017/psrm.2014.46

Every Story Has a Beginning, Middle, and an End (But Not Always in That Order): Predicting Duration Dynamics in a Unified Framework*

DAINA CHIBA, NILS W. METTERNICH AND MICHAEL D. WARD

There are three fundamental duration dynamics of civil conflicts: time until conflict onset, conflict duration, and time until conflict recurrence. Theoretical and empirical models of war usually focus on one or at most two aspects of these three important duration dynamics. We present a new split-population seemingly unrelated duration estimator that treats pre-conflict duration, conflict duration, and post-conflict duration as interdependent processes thus permitting improved predictions about the onset, duration, and recurrence of civil conflict. Our findings provide support for the more fundamental idea that prediction is dependent on a good approximation of the theoretically implied underlying data-generating process. In addition, we account for the fact that some countries might never experience these duration dynamics or become immune after experiencing them in the past.

The end of fighting cannot be equated with eternal peace. As illustrated in Figure 1, 63 percent of civil conflicts recur[1] and we know that a history of armed conflict makes recurrence even more likely (Walter 2004). In the long run we can therefore observe multiple peace and armed conflict spells with varying durations in one and the same conflict (Kreutz 2010). Just reviewing this simple empirical insight already raises the main question of this paper: What is the extent to which pre-conflict, conflict, and post-conflict durations depend on each other? Only recently, scholars are taking seriously the notion 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). However, most empirical efforts to identify the causes of pre-conflict, conflict, and post-conflict durations 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 two unrelated, isolated processes

* Daina Chiba, Lecturer, Department of Government, University of Essex, Colchester, CO4 3SQ (dchiba@essex.ac.uk). Nils W. Metternich, Lecturer, Department of Political Science, University College London, London, WC1H 9QU (n.metternich@ucl.ac.uk). Michael D. Ward, Professor, Department of Political Science, Duke University, Durham, NC 27708 (michael.d.ward@duke.edu). This project was undertaken in the framework of an initiative funded by the Information Processing Technology Office of the Defense Advanced Research Projects Agency aimed at producing models to provide an Integrated Crisis Early Warning Systems (ICEWS) for decision makers in the US defense community. The holding grant is to the Lockheed Martin Corporation, Contract FA8650-07-C-7749. Earlier versions of the paper have been presented at the joint meetings of the Conflict Research Society and European Network for Conflict Research, September 17–20, 2013; the Asian Political Methodology Meeting, January 6–7, 2014, Tokyo; and the UCL Departmental Research Seminar, February 12, 2014. The authors are grateful for the helpful comments they received during and after these presentations. They would also like to thank Andreas Beger, Kentaro Fukumoto, Julian Wucherpfennig, and members of the Ward Lab at Duke University for helpful comments. Nils W. Metternich acknowledges support from the Economic and Social Research Council (ES/L011506/1).

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

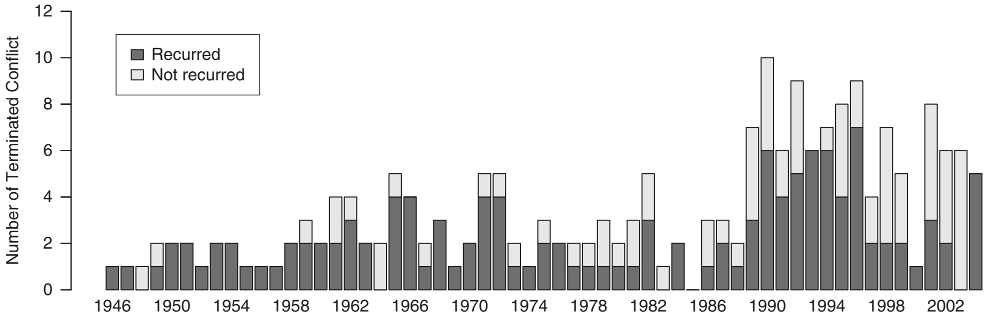

Fig. 1. Conflict recurrence over time, 1946–2004
Note: this figure shows the frequency of conflict recurrence based on the Uppsala Conflict Data Program data set. The height of the bars shows the number of civil conflicts terminated in a given year. The light gray bars show the number of terminated conflicts 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.

(Collier, Hoeffler and Soderbom 2004; Walter 2004; Hegre and Sambanis 2006; Quinn, Mason and Gurses 2007; Balch-Lindsay, Enterline and Joyce 2008). In this paper, we argue that peace (pre- and post-conflict) and conflict durations are interdependent, but highlight that there might be conditions under which actors decide never to fight. For example, if actors expect very high costs of conflict, we should never observe a conflict period. Thus, we have to differentiate between (1) peace spells that are actually at risk of conflict and (2) peace durations that are virtually immune to conflict. We demonstrate that a substantial increase in prediction performance of conflict and post-conflict duration can be achieved by taking into account all aspects of the theoretically implied data-generating process.

Our main contribution is to introduce a split-population (SP) interdependent duration estimator that captures the theoretically implied unobserved interdependence between the durations of pre-conflict peace, conflict, and post-conflict peace. A major goal of this paper is to expand on the current literature that predominantly treats peace and conflict processes as independent (Walter 2009; Blattman and Miguel 2010). Theoretical and empirical research on the determinants of conflict onset (pre-conflict duration) is well developed and probably represents the largest share of existing civil conflict literature (Fearon and Laitin 2003; Collier, Hoeffler and Soderbom 2004; Hegre and Sambanis 2006). Although not to the same extent, our knowledge about conflict durations has greatly expanded in recent years and many factors have been identified that impact on the decisions to continue or end fighting (Balch-Lindsay and Enterline 2000; Fearon 2004; Cunningham 2006). Finally, scholars have been well aware of the fact that it is important to understand the conditions under which conflicts recur and have explored post-conflict durations both theoretically and empirically (Hartzell and Hoddie 2003; Fortna 2003; Walter 2004; Werner and Yuen 2005; Chiba 2015).

Despite the important contributions analyzing conflict and peace durations independently, less research is considering conflict and peace durations as interdependent processes (Hays and Kachi 2011). Although some significant contributions have been made that point to the importance of endogenous processes in conflicts (Reed 2000; Boehmke, Morey and Shannon 2006; Wucherpfennig 2011), the more general conflict literature has not fully embraced the consequences of these duration interdependencies. In addition, when scholars address endogenous conflict processes they focus on the "dyadic duration" interdependence. This means these studies either focus on the relationship between (a) pre-conflict peace and fighting or

TABLE 1 *Existing Duration Studies and Limitations in the Amount of Information Considered*

Study types	**Duration information considered**			**Examples**
Onset studies	Y_1 = Pre-conflictpeace Δ			Beck, Katz and Tucker (1998) Carter and Signorino (2010)
Duration studies		Y_1 = Conflict Δ		Fearon (2004) Cunningham et al. (2009)
Recurrence studies			Y_1 = Post-conflict peace Δ	Fortna (2004) Werner and Yuen (2005)
Selection/Split studies	Y_1 = Pre-conflictpeace Δ	Y_2 = Conflict Δ		Shannon, Morey and Boehmke (2010) Reed (2000)
Interdependent studies		Y_1 = Conflict Δ	Y_2 = Post-conflict peace Δ	Wucherpfennig (2011)
Unifying studies	Y_1 = Pre-conflictpeace Δ	Y_2 = Conflict Δ	Y_1 = Post-conflict peace Δ	Our SPDDD estimator

Note: SPDDD, split-population duration-duration-duration.

(b) fighting and post-conflict peace. Naturally, this gives rise to a sample selection issue. For example, if we take into account the interdependence between conflict duration and post-conflict peace duration, we only allow cases into our sample that have actually experienced conflict. There are many approaches that might take care of this selection effect or split sample. However, the problem with existing approaches is that they take care of selection-duration and split-duration processes, but do not allow us to model what we think is the underlying data-generating process: a split-population duration-duration-duration process.

Consider Table 1 illustrating our three-duration concepts (pre-conflict peace, conflict, and post-conflict peace). Studies that explain conflict onset usually focus on pre-conflict peace and, depending on the research design, may also treat recurrence periods as pre-conflict spells. That implies that any information on conflict duration is not considered. In addition, peace spells are treated as independent and identically distributed and therefore possible interdependence is not considered. This is especially problematic when studies include conflicts with recurrent fighting and peace patterns, because they are likely to be linked to one another. Similarly, studies that focus on conflict duration treat fighting spells as independent from peace spells. A few studies have looked at "dyadic duration" dependence, that is allowing for interdependence between *either* pre-conflict peace spells and conflict spells *or* conflict spells and post-conflict peace spells (Reed 2000; Boehmke, Morey and Shannon 2006; Wucherpfennig 2011). However, each of these empirical approaches does not utilize all observed information. In this paper, we seek to address this limitiation.

Although the empirical assessment of armed conflicts has sidelined interdependent durations, the theoretical literature is well aware of this relationship. Recent formal work on organized violence has conceptualized the onset, continuation, termination, and recurrence of wars as an interrelated bargaining process (Wagner 2000; Filson and Werner 2002; Powell 2004; Leventoglu and Slantchev 2007); however, even though the scholarly community has made considerable progress in developing detailed data sets on various aspects of conflict dynamics over the past decades,[2] the analytical and predictive tools available to the empirical researchers have not yet caught up with the developments in current conflict theories.

We propose a new empirical approach to study phases of peace and conflict in a single, unified survival analysis framework. Survival analysis (also called event history analysis,

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

hazard analysis, or duration analysis) has become a widely used statistical approach to analyze political events (Box-Steffensmeier and Zorn 2001). This approach models the risk of a political event (e.g., conflict, democratization, and leadership change) as a time-dependent process. Survival analysis recognizes that the risk of an event occuring depends on how long the subject has *survived* without previously experiencing the event of interest. Since one can interpret any binary time-series cross-sectional models as an application of survival analysis (Beck, Katz and Tucker 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 this approach to study the duration of conflict (i.e., conflict termination) (e.g., Balch-Lindsay, Enterline and Joyce 2008; Bennett and Stam 1996; Bennett and Stam 1998; Goemans 2000; Regan and Stam 2000; Bueno de Mesquita, Koch and Siverson 2004; Fearon 2004; Slantchev 2004; Krustev 2006; Glassmyer and Sambanis 2008; Ramsay 2008; Cunningham et al. 2009; Langlois and Langlois 2009; Stanley and Sawyer 2009; Shannon, Morey and Boehmke 2010) and the durability of peace after and/or before conflict (i.e., conflict onset and recurrence) (e.g., Werner 1999; Grieco 2001; Fortna 2003; Senese and Quackenbush 2003; Tir 2003; Fortna 2004; Werner and Yuen 2005; Glassmyer and Sambanis 2008; Lo, Hashimoto and Reiter 2008; Quackenbush and Venteicher 2008; Gibler and Tir 2010).

While some efforts have been made to investigate the connection between peace and conflict duration (e.g., Shannon, Morey and Boehmke 2010; Wucherpfennig 2011), less research addresses 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 these three consecutive duration processes jointly. Our estimation strategy is an SP seemingly unrelated duration approach, where we simultaneously estimate whether countries are at risk of experiencing an armed conflict, the pre-conflict peace duration, the conflict duration, and the post-conflict duration. Hence, it is a split-population duration-duration-duration (SPDDD) framework. We conduct empirical analyses of armed conflicts using data from the UCDP over the period from 1946 to 2004.

We propose three major contributions. First, we provide a theoretical argument that implies unobservable factors that impact on the 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 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: INTERDEPENDENT PEACE AND CONFLICT DURATIONS

Unobserved or unmeasurable factors are likely to play an important role in determining peace and conflict duration. At least from a theoretical perspective this is certainly true. For example, bargaining models of war assume that information (Slantchev 2003), power shifts (Powell 2012), fighting costs (Schultz 2001), resolve (Morrow 1989), or patience (Leventoğlu and Tarar, 2008) decisions to begin and end fighting. Empirically, these factors are often difficult to measure as they involve expectations about the future and unobservable concepts.

However, unobservables factors may not only influence a single but multiple processes at the same time. For example, Boehmke (2006) demonstrates that unobserved and unobservable factors influence both the *timing* and *contents* of positions taken by legislators. In addition, Glasgow, Golder and Golder (2012) demonstrate that government formation processes depend heavily on unobservable factors. However, the unobserved and unobservable factors that impact on both peace and conflict duration have received considerably less empirical attention. This seems surprising as peace and conflict are inherently related to each other: peace is interrupted by conflict and conflict is interrupted by peace. We develop a theoretical argument that highlights how a set of unobservable factors that are related to the bargaining environment of actors result in interdependent conflict and peace durations.

Enduring Peace: Immunity from Conflict

Before turning to our argument about duration interdependencies, we want to differentiate between two different peace bargaining situations. (1) Instances where actors are satisfied with the status quo and (2) situations in which at least one actor is unsatisfied with the current state. When actors are satisfied with the status quo, the risk of conflict is theoretically zero. We should not see any fighting, either because the costs of fighting are too high, or the division of the contentious good is in accordance with the underlying power distribution. In such a situation neither side can credibly threaten the other side with the outside option of war and the actors are in a sense "immune" to conflict. Note that actors can be satisfied with the status quo before or after a conflict period. For example, it might be the case that actors actually resolve the contentious issue after some periods of fighting and enter enduring peace (e.g., American Civil War). The existing literature points to several factors that make it more likely that actors are satisfied with the status quo. High economic development is usually associated with the idea that opportunity costs are too high to engage in conflict and actors are more likely to be satisfied with the status quo (Hegre and Sambanis 2006). Democratic societies allow political participation and changes to the status quo without violent means. This allows dissatisfied actors to address their political grievances without resorting to violence. However, stable autocracies can impose high costs for violence and successfully repress opposition forces. This means that so-called "anocracies" should be least immune to conflict (Hegre et al. 2001); however, not only institutional factors should contribute to the immunity of conflict, polices of ethnic exclusion are likely to contribute to the fact that the underlying power relationship is not reflected by the political status of individual groups (Cederman, Wimmer and Min 2010). Ultimately, this will lead to unsatisfied actors that reduce the immunity from conflict.

PROPOSITION 1: When actors are satisfied with the status quo, they are immune from conflict.

Unstable Peace: At Risk of Conflict and Underlying Interdependencies

Having addressed the conditions under which peace endures, we are left with "at-risk" cases where actors are unsatisfied with the status quo. These are situation in which we should see actual crisis bargaining (before conflict) and conflict bargaining (during fighting). To attain some insights on how peace duration and conflict duration are related in the context of these at-risk cases we consider an informational account of bargaining.

Let us consider two actors in a crisis bargaining situation with incomplete information. Leventoğlu and Tarar (2008) give a theoretical account of how the duration of crisis bargaining depends on the patience of the dissatisfied actor. Only in crisis bargaining situations in which the dissatisfied actor is highly patient will long bargaining periods occur. Hence, when a dissatisfied actor values future payoffs, she will wait a long time until an agreement is achieved. Taking the argument of Leventoğlu and Tarar (2008) a bit further, what will happen once the patient dissatisfied actor finds herself in a fighting period? As the patient actor values future payoffs highly, she would not want engage in enduring conflict. The unsatisfied actor should accept an offer after a short period of fighting. Following this line of reasoning that the length of crisis bargaining is driven by the patience of dissatisfied actors, we propose that long periods of crisis bargaining are followed by short periods of fighting.

PROPOSITION 2: Long periods of crisis bargaining are followed by short periods of fighting.

However, the pattern of short peace and conflict durations, and especially recurrent conflict, does not need to arise from the information asymmetry. An alternative account is developed by Powell (2012) where shifts in the underlying power distribution can lead to recurrent patterns of conflict. The rate of these changes will impact the length of fighting and peace spells. Again, unobservable factors drive both peace and conflict durations.

AN SPDDD MODEL

The empirical implications of this paper are tested by implementing a split-population (SP) model that uses seemingly unrelated durations. The seemingly unrelated duration part of the estimator takes into account the theoretically implied endogeneity between peace and conflict duration. The SP part of the model takes into account that there may be unobserved heterogeneity between countries in regard to their predisposition to experience any armed conflict. Hence, there might be some units that are more or less "immune" to initial or recurring conflict and therefore cannot be described by a duration process that assumes that every unit will eventually experience initial or renewed conflict.

We provide Figure 2 to illustrate the importance of accounting for both strategic independence the immunity of units. Let us assume that we can observe some units (e.g., country) over some observation span (e.g., 67 years if our data run from 1946 through 2004). Let us further assume that, at any given point in time, a unit is in either one of two states: peace or in conflict. Survival analysis treats these units as a series of observations that are "at risk" of an event at every point in time until they experience it. In the first two cases (Figure 2: $A1$ and $A2$) the assumption of "at risk" is correct. In case $A1$ the unit is at peace during the observation period and the peace spell also ends within the observation period. For $A2$ the assumption of "at risk" also applies even though the end of the peace spell (failure) is outside of our observation period. This is generally called a right-censored observation. However, for the case of $A3$ the assumption of "at risk" is not met. It will actually never experience failure (conflict) because it is immune. Therefore, we need a SP framework to differentiate between cases like $A1/2$ and $A3$.

However, we not only observe peace spells ($A1$–$A3$) but also peace and conflict spells ($B1$–$B2$). In cases $B1$–$B2$ the "at-risk" assumption holds for both peace and conflict spells because we do not allow for infinite conflict. 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

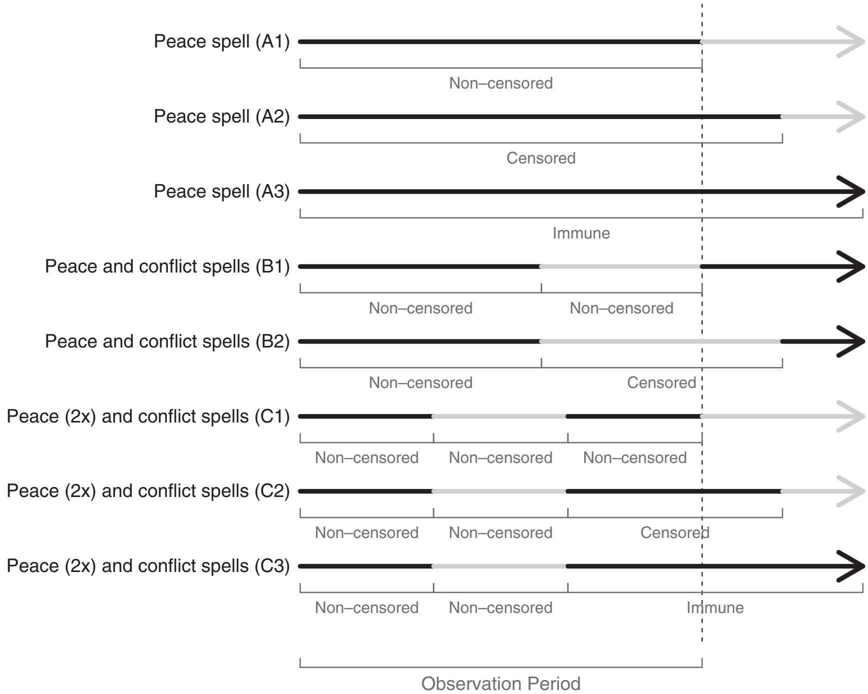

Fig. 2. Conflict data and the differentiation between non-censored, censored, and immune peace spells (black spells)
Note: gray lines represent non-censored and censored conflict spells.

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 t, we say the country experiences a failure at t. In example $B1$, we observe the full length of the peace (black) and conflict spell (gray), whereas in $B2$ the conflict spell is right censored but will fail eventually. Thus the main challenge here is not the "immunity" of units but the theoretically implied interdependency between peace and conflict duration.

Finally, we move to examples $C1 - C3$ in Figure 2. They provide a somewhat realistic picture of recurring peace and conflict spells. In the case of $C1$, we can observe a peace, conflict, and post-conflict peace spell that fails within the observation period. Our theoretical argument proposed that all three spells should be interdependent. This also applies to the cases of $C2$ and $C3$. The main difference between $C2$ and $C3$ is that the latter case will not revert back to conflict in the future. It is in a sense cured from conflict and will not fail. Thus we have to differentiate between cases $C2$ where the "at-risk" assumption holds and $C3$ which violates it.

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 preceding conflict spells in calculating the duration of peace spells and vice versa. Moreover, our proposed model also accommodates the SP 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 peace periods. We derive this model in several steps. We first introduce simple survival models for peace and conflict duration. We then derive the joint duration model that simultaneously estimates peace and conflict duration. Finally, we present a model that jointly estimates the probability of immunity, as well as peace and conflict duration.

For each of the three models, we provide a general model that allows time-varying covariates. That is, in all of our expositions below, the values of the covariates are allowed to vary within a spell. We do so by splitting each spell into shorter observation periods (e.g., year) such that the values of the covariates are constant *within* periods but not across periods. Let $j = 1, \dots, J_s$ index the observation period within a spell s, where there are J_s periods. Let $t_{s,j}$ denote the cumulative duration at period j, where t_{s,J_s} is the total duration of spell s. We evaluate the likelihood contribution for each period rather than for each spell.

Part 1: Simple Duration Model

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

$$\begin{aligned}\Pr\left(T_s^P > t_{s,j}^P \mid T_s^P > t_{s,j-1}^P\right) &= \frac{\Pr\left(T_s^P > t_{s,j}^P \cap T_s^P > t_{s,j-1}^P\right)}{\Pr\left(T_s^P > t_{s,j-1}^P\right)} \\ &= \frac{\Pr\left(T_s^P > t_{s,j}^P\right)}{\Pr\left(T_s^P > t_{s,j-1}^P\right)},\end{aligned} \tag{1}$$

where T_s^P is a random variable that represents the duration of peace spell for s and $t_{s,j}^P$ the cumulative duration of peace for s observed at period j. We treat the observation period j as right censored (even though the spell s may not be ultimately right censored at a later period $j' > j$).

On the other hand, the likelihood contribution from an observation that does experience peace failure at period j is given as

$$\begin{aligned}\Pr\left(T_s^P = t_{s,j}^P \mid T_s^P > t_{s,j-1}^P\right) &= \frac{\Pr\left(T_s^P = t_{s,j}^P \cap T_s^P > t_{s,j-1}^P\right)}{\Pr\left(T_s^P > t_{s,j-1}^P\right)} \\ &= \frac{\Pr\left(T_s^P = t_{s,j}^P\right)}{\Pr\left(T_s^P > t_{s,j-1}^P\right)}.\end{aligned} \tag{2}$$

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

$$L^P \propto \prod \left[\frac{\Pr(T_s^P > t_{s,j}^P)}{\Pr(T_s^P > t_{s,j-1}^P)}\right]^{(r_j=1)} \left[\frac{\Pr(T_s^P = t_{s,j}^P)}{\Pr(T_s^P > t_{s,j-1}^P)}\right]^{(r_j=0)}, \tag{3}$$

where r_j is the (period-level) right-censoring indicator that takes a value of 1 for right-censored periods and 0 for non-censored periods.

To further characterize the likelihood function (3), we specify the probability distribution for the duration variable.[3] Using the flexible Weibull specification,[4] for example, the density function $f(\cdot)$ and the survivor function $S(\cdot)$ are each given as a function of the scale parameter λ and the shape parameter α, as follows:[5]

$$\begin{aligned} \Pr(T = t) &= \lambda\alpha(\lambda t)^{(\alpha - 1)}\exp(-(\lambda t)^{\alpha}) \equiv f(t) \\ \Pr(T > t) &= \exp(-(\lambda t)^{\alpha}) \equiv S(t). \end{aligned} \tag{4}$$

The shape parameter determines whether the risk of "failure" event (i.e., conflict onset) is increasing ($\alpha > 1$), decreasing ($\alpha < 1$), or constant ($\alpha = 1$) over analysis time. We allow the duration of peace to be conditioned on vectors of time-varying covariates, X^P_{sj}. We do so by specifying the scale parameter governing the durations as $\lambda^P_{sj} = \exp(-X^P_{sj}\beta^P)$, where β^P is the vector of coefficient parameters.

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.[6] We can also write down a typical model of conflict duration in a similar manner:

$$L^C \propto \prod \left[\frac{\Pr\left(T^C_s > t^C_{s,j}\right)}{\Pr\left(T^C_s > t^C_{s,j}\right)}\right]^{(r_j=1)} \left[\frac{\Pr\left(T^C_s = t^C_{s,j}\right)}{\Pr\left(T^C_s > t^C_{s,j}\right)}\right]^{(r_j=0)}, \tag{5}$$

where T^C_s is a random variable that represents the duration of conflict for spell s and $t^C_{s,j}$ the cumulative duration of conflict for s observed at period j.

It should be clear from these expositions that a conventional model of peace duration (3) only utilizes information from those observations where conflict is not already ongoing (i.e., cases $A1$ and $A2$ in Figure 2), whereas a conventional model of conflict duration (5) focusses only on observations where conflict is already ongoing. If we believe that peace and conflict spells are interdependent, a separate estimation of equations (3) and (5) is inefficient as each model discards information utilized in the other model. In what follows, we present a seemingly unrelated duration model that allows us to estimate these two processes jointly. This is a stepping stone to our proposed SPDDD model.

Part 2: Joint Model of Pre-Conflict Peace, Conflict, and Post-Conflict Peace Duration

The model we present below takes into account the duration of the preceding spells as well as the duration of the present spell up to the observation period. In other words, the duration of post-conflict peace at period j is formulated as a function of its survival up to $j - 1$ as well as the

[3] There are several different ways to represent a parametric duration model. We follow the parametrization presented in a standard textbook (Box-Steffensmeier and Jones 2004).

[4] We choose Weibull specification here for the purpose of illustration. Analysts can choose other parametric specifications, such as log-logistic specification. We will come back to the issue of model specification in the section on empirical application.

[5] We only show the density and survival functions here, but one can easily characterize some auxiliary functions from these two, such as the distribution function $F(t) = 1 - S(t)$ or hazard function $h(t) = \frac{f(t)}{S(t)}$.

[6] It is true that there is a variation among conflict studies in terms of the observation unit (e.g., country, dyad, and directed dyad), the period-unit (e.g., year, month, or entire spell), and parametric specification of the duration dependence. Nevertheless, any statistical models of conflict onset can be expressed as model (3) with some adjustment.

duration of the conflict that precedes it. In this sense, the model is a seemingly unrelated duration model.

Let $T_s^{C'}$ denote a random variable representing the duration of conflict spell for s that precedes the current peace spell and $t_s^{C'}$ denote a realization of its value. Then, the likelihood contribution from a post-conflict peace observation that experiences peace survival at period 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 $t_s^{C'}$, or

$$\Pr\left[T_s^P > t_{s,j}^P \mid \left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)\right] = \frac{\Pr\left(T_s^P > t_{s,j}^P \cap T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}{\Pr\left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}$$
$$= \frac{\Pr\left(T_s^P > t_{s,j}^P \cap T_s^{C'} = t_s^{C'}\right)}{\Pr\left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}. \tag{6}$$

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

$$\Pr\left[T_s^P = t_{s,j}^P \mid \left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)\right] = \frac{\Pr\left(T_s^P = t_{s,j}^P \cap T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}{\Pr\left(T_s^P = t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}$$
$$= \frac{\Pr\left(T_s^P = t_{s,j}^P \cap T_s^{C'} = t_s^{C'}\right)}{\Pr\left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}. \tag{7}$$

In addition, we specify the likelihood contribution from conflict observations at period j as a function of the preceding peace duration as well as the survival of conflict up to period $j-1$. Let $T_s^{P'}$ denote a random variable representing the duration of peace for s that precedes the current conflict and $t_s^{P'}$ denote its observed value, then we have the following likelihood function that calculates the total likelihood of the data:

$$L \propto \prod \left[\frac{\Pr\left(T_s^P > t_{s,j}^P\right)}{\Pr\left(T_s^P > t_{s,j-1}^P\right)}\right]^{(r_j=1)} \left[\frac{\Pr\left(T_s^P = t_{s,j}^P\right)}{\Pr\left(T_s^P > t_{s,j-1}^P\right)}\right]^{(r_j=0)}$$
$$\left[\frac{\Pr\left(T_{s,j}^C > t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)}{\Pr\left(T_s^C > t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)}\right]^{(r_j=1)} \left[\frac{\Pr\left(T_{s,j}^C = t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)}{\Pr\left(T_s^C > t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)}\right]^{(r_j=0)}$$
$$\left[\frac{\Pr\left(T_s^P > t_{s,j}^P \cap T_s^{C'} = t_s^{C'}\right)}{\Pr\left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}\right]^{(r_j=1)} \left[\frac{\Pr\left(T_s^P = t_{s,j}^P \cap T_s^{C'} = t_s^{C'}\right)}{\Pr\left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right)}\right]^{(r_j=0)}. \tag{8}$$

The first line in the likelihood function (8) calculates the likelihood contribution from pre-conflict peace spells, the second line from the conflict spells, and the last line from post-conflict peace spells.

A challenge in estimating the likelihood function (8) is to characterize two types of joint distributions that appear in the likelihood function (8), 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 would want to model with a non-Normal distribution such as Weibull, log-logistic, or generalized gamma. 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). Scholars have used copula functions to construct models of multiple duration processes (Hays and Kachi 2011; Quiroz Flores 2013), selection models for duration (Boehmke, Morey and Shannon 2006; Chiba, Martin and Stevenson 2015), and joint models of duration and ordered or count variable (Fukumoto forthcoming; Chiba 2015).

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

$$F_{XY}(x, y) = \Pr(X < x \cap Y < y) = C(F_X(x), F_Y(y); \theta), \tag{9}$$

where the association parameter θ represents the degree of interdependence between 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 (9) 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:

$$\begin{aligned}
f_{XY}(x, y) = \Pr(X = x \cap Y = y) &= \frac{\partial C(F_X(x), F_Y(y); \theta)}{\partial x \partial y} \\
&= \frac{\partial C(F_X(x), F_Y(y); \theta)}{\partial F_X(x) \partial F_Y(y)} \cdot f_X(x) \cdot f_Y(y) \\
f_{X|Y}(x, y) = \Pr(X = x | Y = y) &= \frac{\Pr(X = x \cap Y = y)}{\Pr(Y = y)} = \frac{f_{XY}(x, y)}{f_Y(y)}, \\
F_{X|Y}(x, y) = \Pr(X < x | Y = y) &= \int_{-\infty}^{x} f_{X|Y}(x, y),
\end{aligned} \tag{10}$$

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 (8) as

$$\begin{aligned}
\Pr\left(T^A > t^A \cap T^B = t^B\right) &= \Pr\left(T^B = t^B\right) - \Pr\left(T^A < t^A \cap T^B = t^B\right) \\
&= \Pr\left(T^B = t^B\right) \cdot \left[1 - \frac{\Pr(T^A < t^A \cap T^B = t^B)}{\Pr(T^B = t^B)}\right] \\
&= \Pr\left(T^B = t^B\right) \cdot \left[1 - \Pr\left(T^A < t^A \mid T^B = t^B\right)\right] \\
&= f_Y\left(t^B\right) \cdot \left[1 - F_{X|Y}\left(t^A, t^B\right)\right],
\end{aligned} \tag{11}$$

where $f(\cdot)$ is the density function for duration (e.g., Weibull as defined in (4)). The second type of joint probability in (8) is obtained simply as

$$\Pr\left(T^A = t^A \cap T^B = t^B\right) = f_{XY}\left(t^A, t^B\right). \tag{12}$$

To complete the derivation, the last step is to choose a particular copula function for $C(\cdot\,, \cdot; \theta)$ to characterize functions in (9) and (10). 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:

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

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 (10) have the following forms:

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

$$F_{X|Y}(x, y) = \int_{-\infty}^{a} f_{XY}(x, y) = \Phi\left(\frac{a - \theta b}{\sqrt{1-\theta^2}}\right), \tag{13}$$

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.[7] Third, the derivation of the conditional functions in (10) is straightforward with the Gaussian copula.

Bringing it Together: An SPDDD Model

We further extend this joint model by incorporating the SP 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. As "cure" is unobservable, an SP 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

[7] 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 $F^+(u, v) = \min[u, v]$.

a situation where actors are satisfied with the status quo. According to the bargaining perspective, unsatisfied actors (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). SP technique allows us to capture this dynamic by estimating the likelihood of immunity and the conditional risk of conflict given non-immunity.

Let $c_{s,j}$ 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. As we do not observe whether the right-censored country-period observations s,j in the data are immune or not, $c_{s,j}$ is an unobservable variable. When an observation in a peace spell survives period j, the country may be either totally immune from conflict or non-immune (but its time has not come). Then, the likelihood contribution from an observation that experiences peace survival at period 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 that period. We can thus rewrite equation (6) as follows:

$$\begin{aligned}
&\Pr\left[\left\{c_{s,j}=1\cup\left(c_{s,j}=0\cap T_s^P>t_{s,j}^P\right)\right\}\ \middle|\ \left\{c_{s,j}=1\cup\left(c_{s,j}=0\cap T_s^P>t_{s,j-1}^P\cap T_s^{C'}=t_s^{C'}\right)\right\}\right]\\
&\quad=\frac{\Pr\left[c_{s,j}=1\cup\left(c_{s,j}=0\cap T_s^P>t_{s,j}^P\cap T_s^{C'}=t_s^{C'}\right)\right]}{\Pr\left[c_{s,j}=1\cup\left(c_{s,j}=0\cap T_s^P>t_{s,j-1}^P\cap T_s^{C'}=t_s^{C'}\right)\right]}\\
&\quad=\frac{\Pr\left(c_{s,j}=1\right)+\Pr\left(c_{s,j}=0\right)\Pr\left[\left(T_s^P>t_{s,j}^P\cap T_s^{C'}=t_s^{C'}\right)|\,c_{s,j}=0\right]}{\Pr\left(c_{s,j}=1\right)+\Pr\left(c_{s,j}=0\right)\Pr\left[\left(T_s^P>t_{s,j-1}^P\cap T_s^{C'}=t_s^{C'}\right)|\,c_{s,j}=0\right]},
\end{aligned}\tag{14}$$

where $\Pr[(T_s^P>t_{s,j}^P\cap T_s^{C'}=t_s^{C'})\,|\,c_{s,j}=0]$ is the conditional joint probability of post-conflict 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 $c_{s,j}=0$. To calculate the likelihood contribution from such an observation, we rewrite equation (7) as follows:

$$\begin{aligned}
&\Pr\left[c_{s,j}=0\cap T_s^P=t_{s,j}^P\ \middle|\ \left\{c_{s,j}=1\cup\left(c_{s,j}=0\cap T_s^P>t_{s,j-1}^P\cap T_s^{C'}=t_s^{C'}\right)\right\}\right]\\
&\quad=\frac{\Pr\left[c_{s,j}=0\cap T_s^P=t_{s,j}^P\cap T_s^{C'}=t_s^{C'}\right]}{\Pr\left[c_{s,j}=1\cup\left(c_{s,j}=0\cap T_s^P>t_{s,j-1}^P\cap T_s^{C'}=t_s^{C'}\right)\right]}\\
&\quad=\frac{\Pr\left(c_{s,j}=0\right)\Pr\left[\left(T_s^P=t_{s,j}^P\cap T_s^{C'}=t_s^{C'}\right)\ |\ c_{s,j}=0\right]}{\Pr\left(c_{s,j}=1\right)+\Pr\left(c_{s,j}=0\right)\Pr\left[\left(T_s^P>t_{s,j-1}^P\cap T_s^{C'}=t_s^{C'}\right)\ |\ c_{s,j}=0\right]},
\end{aligned}\tag{15}$$

where $\Pr[(T_s^P = t_{s,j}^P \cap T_s^{C'} = t_s^{C'}) \mid c_{s,j} = 0]$ is the conditional joint probability density of post-conflict peace duration given non-immunity.

Our proposed model thus has the following likelihood function:

$$L \propto \prod \left[\frac{\Pr(c_{s,j} = 1) + \Pr(c_{s,j} = 0)\Pr\left(T_s^P > t_{s,j}^P \mid c_{s,j}=0\right)}{\Pr(c_{s,j} = 1) + \Pr(c_{s,j} = 0)\Pr\left(T_s^P > t_{s,j-1}^P \mid c_{s,j}=0\right)} \right]^{(r_j=1)}$$

$$\left[\frac{\Pr(c_{s,j} = 0)\Pr\left(T_s^P = t_{s,j}^P \mid c_{s,j} = 0\right)}{\Pr(c_{s,j} = 1) + \Pr(c_{s,j} = 0)\Pr\left(T_s^P > t_{s,j-1}^P \mid c_{s,j} = 0\right)} \right]^{(r_j=0)}$$

$$\left[\frac{\Pr\left(T_{s,j}^C > t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)}{\Pr\left(T_s^C > t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)} \right]^{(r_j=1)} \left[\frac{\Pr\left(T_{s,j}^C = t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)}{\Pr\left(T_s^C > t_{s,j}^C \cap T_s^{P'} = t_s^{P'}\right)} \right]^{(r_j=0)}$$

$$\left[\frac{\Pr(c_{s,j} = 1) + \Pr(c_{s,j} = 0)\Pr\left[\left(T_s^P > t_{s,j}^P \cap T_s^{C'} = t_s^{C'}\right) \mid c_{s,j} = 0\right]}{\Pr(c_{s,j} = 1) + \Pr(c_{s,j} = 0)\Pr\left[\left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right) \mid c_{s,j} = 0\right]} \right]^{(r_j=1)}$$

$$\left[\frac{\Pr(c_{s,j} = 0)\Pr\left[\left(T_s^P = t_{s,j}^P \cap T_s^{C'} = t_s^{C'}\right) \mid c_{s,j} = 0\right]}{\Pr(c_{s,j} = 1) + \Pr(c_{s,j} = 0)\Pr\left[\left(T_s^P > t_{s,j-1}^P \cap T_s^{C'} = t_s^{C'}\right) \mid c_{s,j} = 0\right]} \right]^{(r_j=0)}, \quad (16)$$

where the first two lines calculate the likelihood contribution from pre-conflict peace observations, the third line from conflict observations, and the last two lines from post-conflict peace observations. We let $c_{s,j}$ be a function of covariates, $X_{s,j}^I$, and use a logit link function such that $\Pr(c_{s,j} = 1) = \left(1 + \exp(-X_{s,j}^I \beta^I)\right)^{-1}$. Therefore, we estimate four equations jointly: one for pre-conflict peace duration, one for conflict duration, one for post-conflict peace duration, and one for immunity.

MONTE CARLO SIMULATION

We demonstrate the performance of this model via Monte Carlo simulations. The analysis reveals that the conventional survival model that ignores immunity status produces biased estimates of the model parameters, even when there is no interdependence between peace and conflict processes. It also shows that, when the processes underlying peace and conflict durations are non-trivially correlated, the SPDDD model outperforms the conventional SP model that estimates peace and conflict durations separately.

A single round of our Monte Carlo simulation consists of 1000 hypothetical country-conflict observations. Each country-conflict has at most three spells: pre-conflict peace spell, conflict spell, and post-conflict peace spell. However, for those observations that are "immune" from conflict, we only observe pre-conflict peace spells. To illustrate the performance of models that recognize the interdependence between peace and conflict, we vary the value of θ from –0.9 (very high negative interdependence between peace and conflict) to 0.9 (very high positive interdependence) with an increment of 0.1. We perform 200 simulations for a given value of θ.

We assume four independent variables influence the process, x_1, x_2, x_3, and x_4. x_1 influences the duration of peace (both pre-conflict and post-conflict), x_2 influences the duration of conflict, and x_3 and x_4 influence the latent immunity status. We generate 1000 values of these four variables, each according to an independent uniform distribution over (−3,3). We hold these variables constant throughout the simulations.

Each round of simulation begins by generating a latent immunity status for each country-conflict i, c_i^*, according to the following specification:

$$c_i^* = -x_3 + x_4 + \eta_i, \tag{17}$$

where η_i follows a logistic distribution. Those observations where $c_i^* > 0$ are immune from conflict and those where $c_i^* \leq 0$ are at risk of conflict. On average, 50 percent of the observations are immune. We then generate two correlated random variables (ν_P,ν_C) for each of the 1000 observations according to a bivariate Normal distribution with a given correlation coefficient θ. To generate peace and conflict durations, we transform ν_m, $m \in \{P,C\}$ into a Weibull variate ϵ_m using the inverse transformation method such that $\epsilon_m = -\log(1-\Phi(\nu_m))$.[8] Then, we generate peace and conflict duration t_m as

$$t_P = \exp(x_1) + \epsilon_P$$

$$t_C = \exp(x_2) + \epsilon_C.$$

For those observations that are immune from conflict (i.e., $c_i > 0$), (1) the pre-conflict peace duration is replaced with a larger value (i.e., the maximum value of t_P in a given round of simulation), (2) the pre-conflict peace is treated as right censored, and (3) conflict and post-conflict peace durations are dropped.

For each set of data, we estimate four sets of models: (1) a simple duration model of peace (pre conflict and post conflict) and conflict, (2) a seemingly unrelated duration model of peace and conflict, (3) SP model of peace, and (4) our developed model, an SPDDD model of peace and conflict. For all of the models, we specify the right-hand side of the equations as follows:

$$\begin{aligned} \text{preconflict peace} &= \beta_{P0} + \beta_{P1} \times x_1 + \beta_{P2} \times x_3 \\ \text{conflict} &= \beta_{C0} + \beta_{C1} \times x_2 \\ \text{postconflict peace} &= \beta_{PC0} + \beta_{PC1} \times x_1 + \beta_{PC2} \times x_3 \\ \text{immunity} &= \beta_{I0} + \beta_{I1} \times x_3 + \beta_{I2} \times x_4. \end{aligned} \tag{18}$$

We are particularly interested in the estimates of β_{P2}. As x_3 only influences the immunity status but not the peace duration in the data-generating process, the true value of β_{P2} is 0. As we will show below, however, models that ignore immunity status will produce estimates far from 0 even in the absence of the interdependence between peace and conflict durations. On the other hand, SP models recover values very close to 0, on average. Furthermore, when there is a non-negligible amount of interdependence between the two duration processes, the seemingly unrelated duration model outperforms the regular SP duration models in terms of root mean squared errors (RMSEs).

We first show the comparison between models with and without an SP component. Figure 3 shows the estimated values of β_{P2} from four models when there is no interdependence between two durations ($\theta = 0$). The density to the left of the figure (in light gray) shows the estimates

[8] We assume that the duration dependence parameter α is equal to 1.

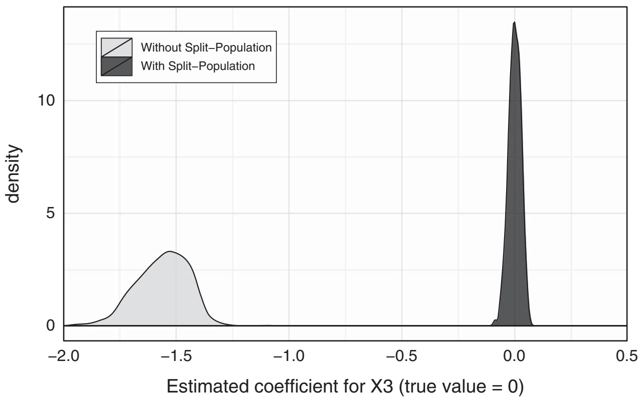

Fig. 3. Bias in estimation
Note: this figure displays the estimated coefficient for x_3 in the pre-conflict peace duration, or β_{P2} in equation (18). The density in light gray to the left of the figure shows the estimates from models without a split-population (SP) component, whereas the density in dark gray to the right of the figure shows the estimates from models with an SP component (standard SP model and our proposed SPDDD model). The figure shows that the estimates from models with an SP component are centered around the true value of $\beta_{P2}(=0)$ but those from models without it are negatively biased.

from the models without SP component (simple duration model and seemingly unrelated duration model).[9] The density to the right of the figure (in dark gray) shows the estimates from the models with an SP component (standard SP duration model and our proposed SPDDD model).[10] We can see that both a standard SP duration and SPDDD models successfully recover the true value of β_{P2}, whereas those without an SP component systematically underestimate it. This is because x_3 negatively influences the immunity status in the data-generating process, as shown in equation (17). As non-immune observations have shorter durations of peace than immune observations, models that ignore the immunity status mistakenly attribute the negative effect of x_3 on immunity to the negative effect of x_3 on peace duration.

What would happen if there exists an interdependence between peace and conflict durations, as our theoretical argument suggests? To illustrate the inefficiency of an approach that ignores the interdependence, we compare our SPDDD model with the simple SP model that estimates peace and conflict durations separately. Although both models successfully recover the true values, *on average*, the simple SP model produces greater amount of estimation errors than does the SPDDD model. Figure 4 shows the ratio of RMSE from the two models for different values of interdependence between durations (θ). Specifically, it shows the RMSE from the SP model divided by the RMSE from the SPDDD model where we vary the value of θ from −0.9 (very high negative dependence) to 0.9 (very high positive dependence). When the two models produce equivalent amount of estimation errors, the ratio is equal to 1. The ratio will be >1 when the SP model produces greater average error compared with the SPDDD model. As we can see in the figure, as θ gets bigger in absolute values, the SP model produces much larger RMSE compared with the SPDDD model.

[9] As the true value of θ in the data-generating process is set equal to 0, the two models produce identical estimates, as expected. We therefore combine the estimates from the two models (200 estimates from each) to simplify the presentation.

[10] Again, estimates from the two models are identical to one another, so we combine the estimates from the two models.

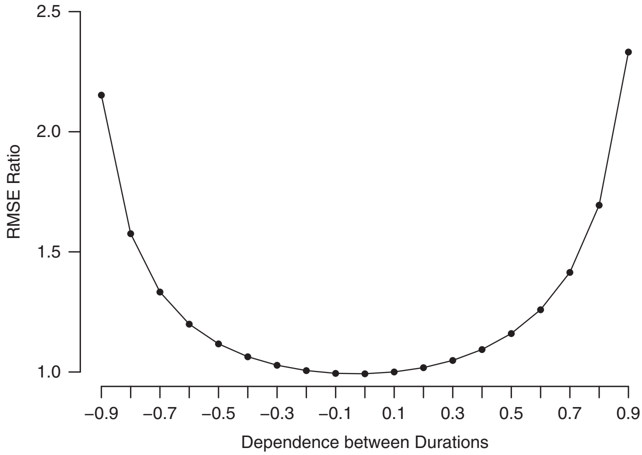

Fig. 4. Efficiency in estimation
Note: this figure shows the ratio of root mean squared error (RMSE) for the simple split-population (SP) model and the split-population duration-duration-duration (SPDDD) model across different values of interdependence between durations. The X-axis denotes the amount of interdependence (θ, varying from −0.9 to 0.9) and the Y-axis shows the RMSE from the SP model divided by the RMSE from the SPDDD model. We can see that, as θ moves away from 0, the SP model produces larger RMSE compared with the SPDDD model.

AN EMPIRICAL APPLICATION

We now turn to an empirical application of our approach to historical data on intrastate conflict from 1946 through 2004. Our sample consists of all independent states as compiled by Gleditsch and Ward (1999).[11] During this period, 177 countries are recognized as independent states. We limit our focus to 166 countries for which reliable information is available at some point during this period.[12] We use information from the UCDP data sets to code intrastate conflict,[13] 99 countries in our sample (59 percent) have experienced at least one intrastate conflict during the observation span, whereas 67 countries (41 percent) have never experienced intrastate conflict.

Peace and Conflict Spells

There are 222 unique conflict spells during the observation span. We define conflict spells as a series of country-day observations where a country experiences at least one ongoing intrastate conflict.[14] The duration of a conflict spell is calculated as the number of days elapsed since the onset of intrastate conflict until its termination or the end of the observation span, December 31, 2004. In our data, there are 19 conflict spells (8.6 percent) where intrastate conflict was still

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

[12] In other words, we drop 11 countries for which information on country-specific characteristics is unavailable for the entire period between 1946 and 2004. The excluded countries are: Barbados, Bhutan, Brunei, East Timor, Iceland, Luxembourg, Maldives, North Yemen, Tibet, Yugoslavia, and Zanzibar.

[13] We used version 4 of the UCDP/PRIO Armed Conflict Data set as well as the UCDP Conflict Termination Data set v.2000-1, available online at http://www.pcr.uu.se/research/UCDP/, accessed 10 January 2014.

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

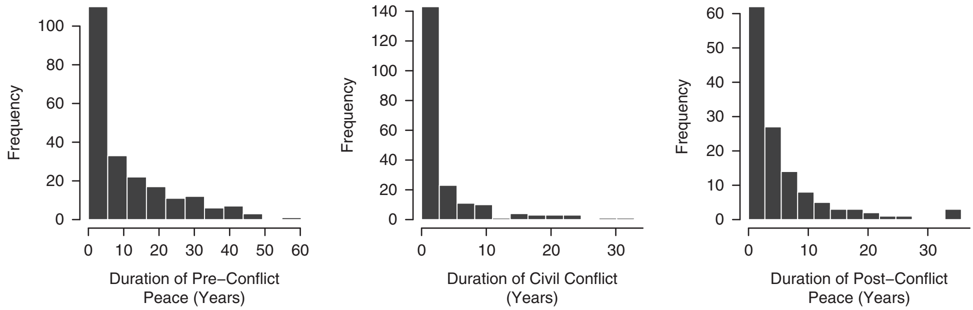

Fig. 5. Duration of peace and civil conflict, 1946–2004
Note: the histogram to the left shows the duration of pre-conflict peace (in years) for the non-censored spells ($n = 222$). The histogram in the middle shows the duration of intrastate conflict (in years) for the non-censored conflict spells ($n = 203$). The histogram to the right shows the duration of post-conflict peace (in years) for the non-censored spells ($n = 129$).

ongoing as of the end date of the observation span. These conflict spells are treated as right censored on December 31, 2004.[15] Therefore, the actual date of conflict termination is observed for the remaining 203 non-censored conflict spells. The duration of conflict spells for the non-censored ones ranges from 1 day to 11,322 days (31 years).[16] The histogram in the middle panel in Figure 5 shows the distribution of conflict duration for the 203 non-censored conflict spells.

For each of the terminated (i.e., non-censored) conflict spells, we calculate the duration of post-conflict peace. A post-conflict peace spell is a series of country-day observations where a country is not experiencing an intrastate conflict. It starts with the termination of an intrastate conflict. As there are 203 non-censored conflict spells, there are 203 post-conflict peace spells. The duration of a post-conflict peace spell is calculated as the number of days elapsed since the termination date of the preceding conflict spell until either one of the following three dates, whichever comes first: (1) the date when another intrastate conflict begins in a country (129 spells or 63 percent); (2) the date when the country lost its independence (two spells or 1 percent); or (3) December 31, 2004 (72 spells or 35 percent).[17] The latter two types of post-conflict spells are treated as right censored. The actual end date of a post-conflict peace spell is observed for the 129 non-censored post-conflict peace process that ended with a recurrence of conflict. The duration of post-conflict spells for the non-censored ones ranges from 1 day to 12,694 days (35 years).[18] The histogram in the right panel in Figure 5 shows the distribution of post-conflict peace duration for the 129 non-censored spells.

Finally, we define pre-conflict peace spells for all the 222 conflict spells as well as for the 63 countries that did not experience any intrastate conflict during the observation span, yielding a sample of 285 pre-conflict peace spells. The starting date of a pre-conflict peace spell is the latest date of the following three dates: (1) the date of termination of the most recent intrastate conflict; (2) the date of independence; or (3) January 1, 1946. The exact duration of a pre-conflict peace spell can be determined only if we get to observe an onset of intrastate conflict. An intrastate conflict breaks out in 222 pre-conflict peace spells (78 percent). For the remaining

[15] In fact, the UCDP data sets provide information up until December 31, 2012. We, nevertheless, choose December 31, 2004 as the censoring point because reliable information on many covariates is available only up to 2004.
[16] The longest conflict spell is observed for Guatemala (1965–1995).
[17] The two countries are South Vietnam (in 1975) and South Yemen (in 1990).
[18] The longest non-censored post-conflict peace spell is observed for Paraguay (1954–1989).

spells, we observe the duration of peace up until December 31, 2004 (61 spells or 21 percent) or the date when the country lost its independence (two spells or 1 percent).[19] We treat these spells as right censored. For the 222 non-censored spells, the duration ranges from 1 day to 20,343 days (56 years).[20] The histogram on the left side in Figure 5 shows the distribution of pre-conflict peace duration for the non-censored spells.

As most of the covariates we introduce below change their values annually, we divide each of the spells into multiple spell-year observations. There are 5370 pre-conflict spell-years (285 pre-conflict spells), 1076 conflict spell-years (222 conflict spells), and 2179 post-conflict spell-years (203 post-conflict spells) in the data.

Covariates

We test the empirical implications of our theoretical argument with a set of variables measuring the characteristics of peace and conflict spells. Before turning to the specification for the duration equations, we present the covariates in the immunity equation. Remember that we argued that satisfied actors are unlikely to begin fighting and hence contribute to immune peace spells. We argued that economic development is associated with satisfied actors and use GDP per capita and controlling for Population to capture this idea. These variables are taken from Fearon and Laitin (2003) and Bleaney and Dimico (2011). We also argued that anocracies are not able to address the needs of unsatisfied actors (like stable democracies) nor can they induce the costs to violence (like stable autocracies). We compose the X-Polity score according to Vreeland (2008), taking the original Polity case format data (Marshall, Gurr and Jaggers 2014) and include the squared term to model the implied curvilinear relationship. Finally, we prepare a dummy variable 1+ excluded that codes whether one or more ethnic groups are excluded from power, as we argued that policies that create gaps between the underlying and actual power distribution are bound to create unsatisfied actors. The data are taken from Cederman, Wimmer and Min (2010).

Theoretically, we are less interested in the specification of the duration equations. This is because our theoretical argument focusses on the importance of unobserved factors. Thus, the main concern is a well-specified model that captures important factors contributed to pre-conflict, conflict, and post-conflict duration.

For conflict spell-years, we use the following covariates. Multilateral conflict takes a value of 1 for conflict spell-years where the government fights with more than one rebel groups, and 0 otherwise. Specifically, this variable is coded 1 when (1) the government fights more than one intrastate conflicts in a given spell-year or (2) the government fights more than one rebel groups in one intrastate conflict in a given spell-year. We rely on information from the UCDP Armed Conflict data set (the Side B variable) in coding this variable and want to capture the robust finding that multiple actors are related to longer conflict duration (Cunningham 2006). Conflict over territory takes the value of 1 for conflict spell-years where the incompatible positions between the government and rebel only concerns territory, and 0 otherwise. We use the Incompatibility variable from the UCDP data set to code these variables, which pertains to the idea that territorial aspects matter for conflict duration (Buhaug, Gates and Lujala 2009). Intensity is also found to be an important predictor of conflict duration (Regan 2002) and is coded 1 for spell-years where the levels of violence exceed the threshold of a civil war according to the UCDP data set. We control for excluded ethnic groups (1+ excluded groups) in

[19] The two countries are East Germany (in 1990) and Czechoslovakia (in 1992).

[20] The longest non-censored pre-conflict peace spell is observed for the United States of America (1946–2001).

line with empirical support for the notion that ethnic exclusion impacts on conflict duration (Wucherpfennig et al. 2012). Resources are frequently argued to affect conflict dynamics and we control for the occurrence of Diamonds and on-shore Oil. We also account for the political institutions (X-Polity) and whether the conflict has taken place during the Cold War.

For pre-conflict peace spells we introduce a similar set of covariates as in the immunity equation. We do this because the current literature does not systematically distinguish between factors that contribute to the immunity of conflict or the length of peace spell in at-risk cases. However, we argue that lootable resources can lead to a quicker onset of fighting if a country is at risk of conflict. Hence, our model includes Diamonds and on-shore Oil coded 1 for countries with such and 0 otherwise. More generally, the main explanatory variables that we introduce in the immunity and pre-conflict duration equation are similar to the main explanatory variables in civil conflict onset studies (Hegre et al. 2001; Fearon and Laitin 2003; Cederman, Wimmer and Min 2010).

Finally, for post-conflict peace spells we especially focus on the outcome of the previous conflict. It is frequently argued that especially government victories increase the duration of post-conflict peace and empirical support for this argument seems to be robust (Toft 2010). We use information from the UCDP Conflict Termination Data set to code how the preceding conflict is terminated. 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. 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/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. This leaves No/Low Intensity outcomes as the baseline category. We also control for regime type (X-Polity, economic development (per capita GDP), Population, and natural resources (Oil coded 1 for countries with on-shore oil wells and 0 otherwise, Diamond coded 1 for countries with diamond mines and 0 otherwise). Finally, we account for politically excluded ethnic groups in the post-conflict peace period (1+ excluded groups).

We impute the missing values of the structural variables using the semi-parametric imputation technique proposed by Hoff (2007).

EMPIRICAL RESULTS

Table 2 shows the estimated coefficients from four models. The first column reports the results from a simple duration model of peace and conflict.[21] These results correspond to the results typically reported in conflict research that assumes as if the two processes were unrelated. The second column reports the results from a seemingly unrelated duration model of peace and conflict that recognizes the interdependence between peace and conflict, whereas still ignoring immunity status. The third column reports the results from a simple SP model that accounts for immunity but ignores the interdependence. Finally, the fourth column reports the results from our SPDDD model. 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

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

TABLE 2 *Results from Four Different Models*

	Simple	SUD	SP	SPDDD
Pre-conflict peace duration				
Constant	9.63 (0.00)	9.62 (0.00)	9.50 (0.00)	9.43 (0.00)
Per capita GDP (logged)	0.21 (0.02)	0.22 (0.02)	0.15 (0.12)	0.15 (0.11)
X-Polity	–0.06 (0.03)	–0.05 (0.04)	–0.05 (0.09)	–0.04 (0.10)
X-Polity^2	0.04 (0.00)	0.04 (0.00)	0.01 (0.09)	0.01 (0.11)
Population (logged)	–0.27 (0.00)	–0.27 (0.00)	–0.26 (0.00)	–0.25 (0.00)
Diamonds	–0.20 (0.40)	–0.19 (0.42)	–0.20 (0.37)	–0.18 (0.43)
Oil	–0.27 (0.21)	–0.27 (0.20)	–0.26 (0.26)	–0.27 (0.24)
There exist 1+ excluded groups	–0.53 (0.03)	–0.52 (0.04)	0.30 (0.26)	0.31 (0.24)
log (α) (duration dependence)	–0.25 (0.00)	–0.25 (0.00)	–0.17 (0.01)	–0.16 (0.01)
Conflict duration				
Constant	4.30 (0.01)	4.04 (0.02)	4.30 (0.01)	3.61 (0.04)
Per capita GDP (logged)	–0.11 (0.56)	–0.10 (0.60)	–0.11 (0.56)	–0.07 (0.72)
Population (logged)	0.22 (0.06)	0.24 (0.05)	0.22 (0.06)	0.27 (0.03)
Multilateral conflict	1.28 (0.00)	1.26 (0.00)	1.28 (0.00)	1.23 (0.00)
Intensity	0.83 (0.03)	0.82 (0.03)	0.83 (0.03)	0.80 (0.03)
Conflict over territory	0.66 (0.04)	0.62 (0.06)	0.66 (0.04)	0.57 (0.09)
X-Polity	0.06 (0.13)	0.07 (0.11)	0.06 (0.13)	0.07 (0.10)
X-Polity^2	0.00 (0.80)	0.00 (0.90)	0.00 (0.80)	0.00 (0.88)
Diamonds	–0.17 (0.66)	–0.14 (0.72)	–0.17 (0.66)	–0.10 (0.80)
Oil	–0.23 (0.49)	–0.26 (0.45)	–0.23 (0.49)	–0.29 (0.39)
Cold War	0.25 (0.41)	0.28 (0.35)	0.25 (0.41)	0.34 (0.27)
There exist 1+ excluded groups	0.70 (0.08)	0.72 (0.07)	0.70 (0.08)	0.61 (0.13)
log (α) (duration dependence)	–0.68 (0.00)	–0.68 (0.00)	–0.68 (0.00)	–0.68 (0.00)
Post-conflict peace duration				
Constant	5.94 (0.00)	5.94 (0.00)	7.10 (0.00)	7.03 (0.00)
Per capita GDP (logged)	0.47 (0.00)	0.47 (0.00)	0.27 (0.07)	0.25 (0.08)
Rebel victory	0.96 (0.01)	0.98 (0.01)	0.57 (0.13)	0.59 (0.11)
Government victory	–0.22 (0.55)	–0.14 (0.71)	–0.23 (0.56)	–0.11 (0.77)
Peace agreement	0.40 (0.21)	0.40 (0.21)	0.34 (0.29)	0.36 (0.26)
Conflict over territory	–0.45 (0.08)	–0.46 (0.08)	–0.58 (0.02)	–0.59 (0.02)
Population (logged)	–0.04 (0.69)	–0.04 (0.66)	–0.11 (0.25)	–0.10 (0.27)
X-Polity	–0.02 (0.49)	–0.02 (0.48)	0.00 (0.96)	0.00 (0.95)
X-Polity^2	0.01 (0.20)	0.01 (0.20)	0.01 (0.28)	0.01 (0.37)
Diamonds	–0.17 (0.61)	–0.18 (0.60)	–0.39 (0.22)	–0.39 (0.21)
Oil	–0.64 (0.03)	–0.62 (0.04)	–0.55 (0.07)	–0.54 (0.08)
There exist 1+ excluded groups	–0.71 (0.03)	–0.71 (0.03)	0.43 (0.40)	0.49 (0.31)
log (α) (duration dependence)	–0.22 (0.00)	–0.22 (0.00)	–0.11 (0.19)	–0.11 (0.17)
Immunity				
Constant			–5.47 (0.08)	–5.08 (0.07)
There exist 1+ excluded groups			–2.83 (0.00)	–2.68 (0.00)
Per capita GDP (logged)			0.55 (0.03)	0.55 (0.02)
X-Polity			–0.15 (0.03)	–0.14 (0.03)
X-Polity^2			0.08 (0.00)	0.08 (0.00)
Population			–0.14 (0.56)	–0.18 (0.38)
$\tanh^{-1}(\theta)$ (interdependence)		–0.05 (0.46)		–0.10 (0.13)
Log-likelihood	4907	4907	4893	4892
AIC	9884	9886	9869	9868

Note: SP, split population; SPDDD, split-population duration-duration-duration; AIC, Akaike Information Criterion.
p-values (two-tailed test) in parentheses.

second, third, and fourth models and the second and third models are each nested in the fourth model. We can see that our SPDDD model yields the lowest AIC score of all the four models, suggesting that it fits the data better than the other three models.

As we noted previously, two parametric specifications are used to describe the duration processes of peace and conflict: Weibull parametrization and log-logistic parametrization. Weibull parametrization is a simple and flexible specification where the underlying failure risk (i.e., hazard) is allowed to increase, decrease, or be constant. One limitation of the Weibull specification, however, is that it does not allow for non-monotonic change in hazard. Therefore, we also use log-logistic parametrization that allows for non-monotonicity (but not a monotonic increase) in hazard. We choose between Weibull and log-logistic parametrization based on fit statistics. Coefficients shown in Table 2 are those with Weibull parametrization.[22]

As the models have (at most) four equations, there are four sets of coefficients. The first three sets are the estimated parameters for pre-conflict peace duration, conflict duration, and post-conflict peace duration. The coefficients are represented in the accelerated failure time metric; positive estimates are associated with longer duration. Estimates for duration dependence parameters, α, are shown at the bottom of each set.[23] The fourth set shows the estimates for the immunity equation for models with an SP component. Variables with positive estimates are associated with higher likelihood that the country is immune from conflict. Finally, estimates for the correlation parameter θ, are shown near the bottom of the table.[24]

We can see that the estimated correlation parameter $\tanh^{-1}(\theta)$ is negative, generating $\theta = -0.1$ in our SPDDD model. This suggests that peace duration and conflict duration are negatively correlated, conditional on the covariates and our model specifications. In other words, conflicts following longer (shorter) peace tends to be shorter (longer) and post-conflict peace following longer (shorter) conflict tends to be shorter (longer). This finding is consistent with our theoretical expectation. The estimated log (α) for conflict spells is negative, generating $\alpha < 1$. This suggests that the risk of conflict termination is decreasing over time, other things being equal. The estimated log (α) for pre-conflict and post-conflict peace spells are both negative but with larger standard errors for post-conflict peace periods in the SPDDD model. This result implies that we have evidence to suggest that the conditional risk of conflict onset given "non-immunity" is decreasing over time, controlling for the covariates and the interdependence of conflict and peace duration.

Some striking differences are observed between models with and without an SP component. As we show with Monte Carlo simulations, models that ignore immunity status underestimate (overestimate) the effect of covariates that negatively (positively) influence immunity. For example, SP and SPDDD models suggest that the presence of excluded ethnic groups (1) makes a country less likely to be immune from conflict but (2) does not necessarily influence post-conflict peace duration (the p-values of excluded groups increase in the SP and SPDDD models). As we discussed in the theoretical section, factors such as the absence of ethnic groups excluded from a country's political process represent the absence of unsatisfied actors willing to fight. Furthermore, we can see that 1+ excluded groups, GDP per capita and X-Polity have the expected effects on immunity from conflict. Richer countries are less likely to experience any conflict, whereas anocracies and countries with excluded ethnic groups are more likely to be at risk of conflict.

To demonstrate the better fit of our proposed model, we calculate the expected duration for uncensored peace and conflict spells according to our SPDDD model and the simple

[22] The log-logistic model generates AIC score of 9880, whereas AIC for the Weibull model is 9868. We thus chose Weibull–Weibull specification as it generates the lower AIC score.

[23] Note that α is re-parameterized as log (α). This is necessary because the duration dependence α can only take positive values.

[24] Note that θ is re-parameterized as $\tanh^{-1}(\theta)$. This is necessary because the correlation θ is only defined between -1 and 1.

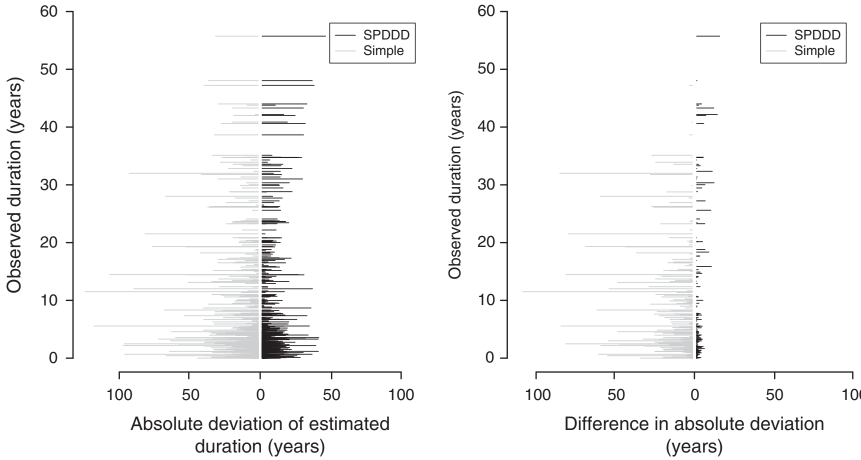

Fig. 6. In-sample prediction assessment
Note: this figure compares model fit and in-sample prediction between simple Weibull model and the split-population duration-duration-duration (SPDDD) model. The left panel shows the absolute deviation of the predicted duration for the two models, whereas the right panel shows the difference in absolute deviation. In each panel, gray lines (plotted to the left) refer to Simple model whereas black lines (plotted to the right) refer to the SPDDD model.

duration model. For our sample, the SPDDD model yielded predicted values closer to the observed values 60 percent of the time (330 out of 554 uncensored spells). Moreover, the deviation of prediction from the observed duration is much smaller for the SPDDD model than for the simple model. Figure 6 illustrates this point. In each panel, plotted to the left (in gray lines) are estimates from the simple model, whereas plotted to the right are estimates from the SPDDD model. The left panel shows the absolute deviation of predicted duration from the observed duration for all non-censored spells in our data set. The Y-axis shows the observed duration, and the X-axis shows the absolute difference between the observed and predicted duration from the two model. We can see that the simple model often yields deviation as large as 50 years, whereas the SPDDD model never yields deviation >50 years and seldom yields deviation as large as 25 years. The right panel of the figure illustrates the advantage of SPDDD model in terms of the difference in prediction error between the SPDDD model and the simple model. Lines to the left (in gray) show the absolute deviation (observed–predicted) from the simple model minus the absolute deviation from the SPDDD model for the cases where SPDDD performs better than the simple. Similarly, the lines to the right (in black) show the absolute deviation (observed–predicted) from the SPDDD model minus the absolute deviation from the simple model for the cases where the simple model performs better than the SPDDD model. We can see clearly that the SPDDD model performs better than the simple model most of the times and by a great extent.[25]

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

[25] Superior model fit can also be demonstrated by comparing RMSE estimates for the two models. RMSE estimates from the SPDDD model are 5332 (days) for the pre-conflict peace process (as opposed to 10,917 for the simple model), 3436 for the post-conflict process (as opposed to 7145 for the simple model), and 3104 for the conflict process (as opposed to 3121 for the simple model).

duration, conflict duration, and post-conflict peace duration as interdependent processes. Our main argument is that we should account for the unobserved status of immunity from conflict as well as the unobserved factors that generate an interdependence between pre-conflict, conflict, and post-conflict processes.

Herein, we introduced an estimation approach that captures important elements of our theoretical argument. Our Monte Carlo simulations confirm that a failure to account for the unobserved immunity and/or interdependence leads to biased inferences. The empirical results also demonstrate that a model that corrects for these two inferential problems provides a better model fit. Our proposed model not only fits the data better but also reveals that some of the covariates that were thought to influence peace *duration* also influence the immunity from conflict. In fact, some estimates, especially the political exclusion of ethnic groups, become less precise in the peace duration equations once we account for the possible immunity of cases. Although ethnic exclusion consistently impacts on conflict duration (Wucherpfennig et al. 2012) (even though in the SPDDD model less precise (p-value = 0.13)), its effect is less certain in regard to pre- (p-value = 0.24) or post-conflict peace duration (p-value = 0.31). Similar observations can be made for GDP per capita. Of course, we are cautious about a final interpretation of these results as further research has to provide insights into whether the underlying assumption of the SP model that the immunity process is uncorrelated with the duration processes needs to be relaxed.

A further important insight of our work is that although peace and conflict durations seem to be related through unobserved factors, the main predictive improvement of our empirical model comes from modeling whether or not countries are immune from initial or further conflict. According to our theoretical argument, this would imply that once we account for whether actors are unsatisfied with the status quo, we can improve the actual duration modeling. In fact going back to our empirical model, there is evidence that once we model the immunity of cases, we also get more precise estimates for the interdependence between durations (θ p-value SUD = 0.46; θ p-value SPDDD = 0.13) and a decrease in the AIC score (SUD = 9886; SPDDD = 9868). This again highlights the importance of modeling the theoretically implied data-generating process as closely as possible. We believe that our empirical results support the case for further research focussing on both the interdependent nature of durations and the immunity of certain cases from conflict.

REFERENCES

Balch-Lindsay, Dylan, and Andrew J. Enterline. 2000. 'Killing Time: The World Politics of Civil War Duration, 1820–1992'. *International Studies Quarterly* 44(4):615–42.

Balch-Lindsay, Dylan, Andrew J. Enterline, and Kyle A. Joyce. 2008. 'Third-Party Intervention and the Civil War Process'. *Journal of Peace Research* 45(3):345–63.

Beck, Nathaniel, Jonathan N. Katz, and Richard Tucker. 1998. 'Taking Time Seriously: Time-Series-Cross-Section Analysis with a Binary Dependent Variable'. *American Journal of Political Science* 42(4):1260–88.

Bennett, D. Scott, and Allan C. Stam. 1996. 'The Duration of Interstate Wars'. *American Political Science Review* 90(2):239–57.

——. 1998. 'The Declining Advantages of Democracy'. *Journal of Conflict Resolution* 42(3):344–66.

Blattman, Christopher, and Edward Miguel. 2010. 'Civil War'. *Journal of Economic Literature* 48(1): 3–57.

Bleaney, Michael, and Arcangelo Dimico. 2011. 'How Different are the Correlates of Onset and Continuation of Civil Wars?'. *Journal of Peace Research* 48(2):145–55.

Boehmke, Frederick J. 2006. 'The Influence of Unobserved Factors on Position: Timing and Content in the NAFTA Vote'. *Political Analysis* 14(4):421–38.

Boehmke, Frederick J., Daniel S. Morey, and Megan Shannon. 2006. 'Selection Bias and Continuous-Time Duration Models: Consequences and a Proposed Solution'. *American Journal of Political Science* 50(1):192–207.

Box-Steffensmeier, Janet M., and Bradford S. Jones. 2004. *Event History Modeling: A Guide for Social Scientists*. Cambridge, UK: Cambridge University Press.

Box-Steffensmeier, Janet M., and Christopher J. W. Zorn. 2001. 'Duration Models and Proportional Hazards in Political Science'. *American Journal of Political Science* 45(4):972–88.

Bueno de Mesquita, Bruce, Michael Koch, and Randolph Siverson. 2004. 'Testing Competing Institutional Explanations of the Democratic Peace: The Case of Dispute Duration'. *Conflict Management and Peace Science* 21(4):255–67.

Buhaug, H., Scott Gates, and Päivi Lujala. 2009. 'Geography, Rebel Capability, and the Duration of Civil Conflict'. *Journal of Conflict Resolution* 53(4):544–69.

Carter, David B., and Curtis S. Signorino. 2010. 'Back to the Future: Modeling Time Dependence in Binary Data'. *Political Analysis* 18(3):271–92.

Cederman, Lars-Erik, Andreas Wimmer, and Brian Min. 2010. 'Why Do Ethnic Groups Rebel? New Data and Analysis'. *World Politics* 62(1):87–119.

Chiba, Daina. 2015. 'The Strength of Cease-Fire Agreements and the Duration of Postwar Peace'. Unpublished manuscript, University of Essex.

Chiba, Daina, Lanny W. Martin, and Randolph T. Stevenson. 2014. 'A Copula Approach to the Problem of Selection Bias in Models of Government Survival'. *Political Analysis* 23(1):42–58.

Collier, Paul, Anke Hoeffler, and Mans Soderbom. 2004. 'On the Duration of Civil War'. *Journal of Peace Research* 41(3):253–73.

Cunningham, David E. 2006. 'Veto Players and Civil War Duration'. *American Journal of Political Science* 50(4):875–92.

Cunningham, David E., Kristian Skrede Gleditsch, and Idean Salehyan. 2009. 'It Takes Two: A Dyadic Analysis of Civil War Duration and Outcome'. *Journal of Conflict Resolution* 53(4): 570–97.

Fearon, James D. 1995. 'Rationalist Explanations for War'. *International Organization* 49(3):379–414.

——. 2004. 'Why Do Some Civil Wars Last So Much Longer than Others?'. *Journal of Peace Research* 41(3):275–301.

Fearon, James D., and David D. Laitin. 2003. 'Ethnicity, Insurgency, and Civil War'. *American Political Science Review* 97(1):75–90.

Filson, Darren, and Suzanne Werner. 2002. 'A Bargaining Model of War and Peace: Anticipating the Onset, Duration and Outcome of War'. *American Journal of Political Science* 46(4):819–38.

Fortna, Virginia Page. 2003. 'Scraps of Paper? Agreements and the Durability of Peace'. *International Organization* 57(2):337–72.

——. 2004. *Peace Time: Cease-Fire Agreements and the Durability of Peace*. Princeton, NJ: Princeton University Press.

Fukumoto, Kentaro. forthcoming. 'What Happens Depends on When It Happens: Copula-Based Ordered Event History Analysis of Civil War Duration and Outcome'. *Journal of the American Statistical Association*.

Gibler, Douglas M., and Jaroslav Tir. 2010. 'Settled Borders and Regime Type: Democratic Transitions as Consequences of Peaceful Territorial Transfers'. *American Journal of Political Science* 54(4): 951–68.

Glasgow, Garrett, Matt Golder, and Sona N. Golder. 2012. 'New Empirical Strategies for the Study of Parliamentary Government Formation'. *Political Analysis* 20(2):248–70.

Glassmyer, Katherine, and Nicholas Sambanis. 2008. 'Rebel–Military Integration and Civil War Termination'. *Journal of Peace Research* 45(3):365–84.

Gleditsch, Kristian S., and Michael D. Ward. 1999. 'Interstate System Membership: A Revised List of the Independent States Since 1816'. *International Interactions* 25(4):393–413.

Goemans, Hein E. 2000. 'Fighting for Survival'. *Journal of Conflict Resolution* 44(5):555–79.

Grieco, Joseph M. 2001. 'Repetitive Military Challenges and Recurrent International Conflicts, 1918-1994'. *International Studies Quarterly* 45(2):295–316.

Hartzell, Caroline, and Matthew Hoddie. 2003. 'Institutionalizing Peace: Power Sharing and Postcivil War Conflict Management'. *American Journal of Political Science* 47(2):318–32.

Hays, Jude C., and Aya Kachi. 2011. 'Interdependent Duration Models in Political Science: Existing Strategies for Modeling Interdependent Durations', Unpublished manuscript, University of Illinois.

Hegre, Havard, and Nicholas Sambanis. 2006. 'Sensitivity Analysis of Empirical Results on Civil War Onset'. *Journal of Conflict Resolution* 50(4):508–35.

Hegre, Håvard, Tanja Ellingsen, Scott Gates, and Nils Petter Gleditsch. 2001. 'Toward a Democratic Civil Peace? Democracy, Political Change, and Civil War, 1816–1992'. *American Political Science Review* 95(1):33–48.

Hoff, Peter D. 2007. 'Extending the Rank Likelihood for Semiparametric Copula Estimation'. *The Annals of Applied Statistics* 1(1):265–83.

Kreutz, Joakim. 2010. 'How and When Armed Conflicts End: Introducing the UCDP Conflict Termination Dataset'. *Journal of Peace Research* 47(2):243–50.

Krustev, Valentin L. 2006. 'Interdependence and the Duration of Militarized Conflict'. *Journal of Peace Research* 43(3):243–60.

Leventoğlu, Catherine C, and Jean-Pierre P. Langlois. 2009. 'Does Attrition Behavior Help Explain the Duration of Interstate Wars? A Game Theoretic and Empirical Analysis'. *International Studies Quarterly* 53:1051–73.

Leventoğlu, Bahar, and Ahmer Tarar. 2008. 'Does Private Information Lead to Delay or War in Crisis Bargaining?'. *International Studies Quarterly* 52(3):533–53.

——, and Branislav L. Slantchev. 2007. 'The Armed Peace: A Punctuated Equilibrium Theory of War'. *American Journal of Political Science* 51(4):755–71.

Lo, Nigel, Barry Hashimoto, and Dan Reiter. 2008. 'Ensuring Peace: Foreign-Imposed Regime Change and Postwar Peace Duration, 1914–2001'. *International Organization* 62(4):717–36.

Marshall, Monty G., Ted Robert Gurr, and Keith Jaggers. 2014. 'Polity IV Project: Political Regime Characteristics and Transitions, 1800–2013 Dataset Users' Manual', Available at http://www.systemicpeace.org/inscr/p4manualv2013.pdf, accessed January 2015.

Morrow, James D. 1989. 'Capabilities, Uncertainty, and Resolve: A Limited Information Model of Crisis Bargaining'. *American Journal of Political Science* 33(4):941–72.

Powell, Robert. 2004. 'Bargaining and Learning While Fighting'. *American Journal of Political Science* 48(2):344–61.

——. 2006. 'War as a Commitment Problem'. *International Organization* 60(1):169–203.

——. 2012. 'Persistent Fighting and Shifting Power'. *American Journal of Political Science* 56(3): 620–37.

Quackenbush, Stephen L., and Jerome F. Venteicher. 2008. 'Settlements, Outcomes, and the Recurrence of Conflict'. *Journal of Peace Research* 45(6):723–42.

Quinn, J. Michael, T. David Mason, and Mehmet Gurses. 2007. 'Sustaining the Peace: Determinants of Civil War Recurrence'. *International Interactions* 33(2):167–93.

Quiroz Flores, Alejandro. 2013. 'Testing Copula Functions as a Method to Derive Bivariate Weibull Distributions'. Unpublished manuscript, University of Essex.

Ramsay, Kristopher W. 2008. 'Settling it on the Field: Battlefield Events and War Termination'. *Journal of Conflict Resolution* 52(6):850–79.

Reed, William. 2000. 'A Unified Statistical Model of Conflict Onset and Escalation'. *American Journal of Political Science* 44(1):469–84.

Regan, Patrick M.. 2002. 'Third Party Interventions and the Duration of Intrastate Conflicts'. *Journal of Conflict Resolution* 46(1):55–73.

Regan, Patrick M., and Allan C. Stam. 2000. 'In the Nick of Time: Conflict Management, Mediation Timing, and the Duration of Interstate Disputes'. *International Studies Quarterly* 44:239–60.

Schultz, Kenneth. 2001. 'Looking for Audience Costs'. *Journal of Conflict Resolution* 45:32–60.

Senese, Paul D., and Stephen L. Quackenbush. 2003. 'Sowing the Seeds of Conflict: The Effect of Dispute Settlements on Durations of Peace'. *The Journal of Politics* 65(3):696–717.

Shannon, Megan, Daniel Morey, and Frederick J. Boehmke. 2010. 'The Influence of International Organizations on Militarized Dispute Initiation and Duration'. *International Studies Quarterly* 54(4):1123–41.

Slantchev, Branislav L. 2003. 'The Power to Hurt: Costly Conflict with Completely Informed States'. *American Political Science Review* 97(1):123–33.

——. 2004. 'How Initiators End Their Wars: The Duration of Warfare and the Terms of Peace'. *American Journal of Political Science* 48(4):813–29.

Stanley, Elizabeth A., and John P. Sawyer. 2009. 'The Equifinality of War Termination: Multiple Paths to Ending War'. *Journal of Conflict Resolution* 53(5):651–76.

Svolik, Milan. 2008. 'Authoritarian Reversals and Democratic Consolidation'. *American Political Science Review* 102(2):153–68.

Tir, Jaroslav. 2003. 'Averting Armed International Conflicts Through State-to-State Territorial Transfers'. *Journal of Politics* 65(4):1235–57.

Toft, Monica Duffy. 2010. *Securing the Peace: The Durable Settlement of Civil Wars*. Princeton, NJ: Princeton University Press.

Trivedi, Pravin K., and David M. Zimmer. 2005. *Copula Modeling*: *An Introduction for Practitioners*. Boston, MA: Now Publishers Inc.

Vreeland, James Raymond. 2008. 'The Effect of Political Regime on Civil War: Unpacking Anocracy'. *Journal of Conflict Resolution* 52(3):401–25.

Wagner, R. Harrison. 2000. 'Bargaining and War'. *American Journal of Political Science* 44(3):469–84.

Walter, Barbara F. 2004. 'Does Conflict Beget Conflict? Explaining Recurring Civil War'. *Journal of Peace Research* 41(3):371–88.

——. 2009. 'Bargaining Failures and Civil War'. *Annual Review of Political Science* 12:243–61.

Werner, Suzanne. 1999. 'The Precarious Nature of Peace: Resolving the Issues, Enforcing the Settlement, and Renegotiating the Terms'. *American Journal of Political Science* 43(3):912–34.

Werner, Suzanne, and Amy Yuen. 2005. 'Making and Keeping Peace'. *International Organization* 59(2):261–92.

Wucherpfennig, Julian. 2011. 'Endogenizing Power-Sharing After Ethno-Nationalist Conflict'. Unpublished manuscript, ETH, Zurich.

Wucherpfennig, Julian, Nils W. Metternich, Lars-Erik Cederman, and Kristian Skrede Gleditsch. 2012. 'Ethnicity, the State, and the Duration of Civil War'. *World Politics* 64(1):79–115.