Extended Appendix for Democracy and Civil War

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This document serves as an extended appendix for the chapter "Democracy and Civil War" in *The Handbook of War Studies* (Midlarsky, ed., 2007), written by Nils Petter Gleditsch, Håvard Hegre, and Håvard Strand. The chapter is published with a short appendix, outlining the most important features of the research design. This document add a thorough explanation of the statistical methods used in the Chapter, both focusing on why they where chosen and how (and why) the coefficients should be interpreted.

Research Design

This document serves as an extended appendix for the chapter "Democracy and Civil War" in *The Handbook of War Studies* (Midlarsky, ed., 2007). The questions raised in that chapter are comparative in nature. They do not predict the actual level of conflict in democracies, but argue that, relative to other regimes, democracies are in general more peaceful. Setting up a large-N comparative design capable of evaluating these claims can be challenging, since it is not always clear what we should compare with what. We will here initially discuss how the comparative setup is highly dependent on theoretic nature of the argument presented, and show why this chapter indeed must employ a number of different designs. We will then go on to discuss some methodological pitfalls which can obscure our intentions and in effect covertly bar us from comparing the units we are interested in. The final section will in detail discuss the actual econometric setup used.

We have discussed the difference between studies that focus on *onset* and *incidence*. Whereas these terms refer to the same phenomenon, they are quite different with regard to time. A conflict onset is a transition from a state of peace to a state of war, and is commonly thought of as an event. On the other hand, incidence of conflict corresponds to a state of conflict, which, in contrast to onsets, have both an initiation but also a duration. A state of conflicts lasts for some time, and an analysis of incidence is therefore both an inquiry into what makes conflicts begin and what makes them endure. If our theory says that the same factors both initiate and prolong conflict, then an incidence design might be a sensible choice. If we on the other hand believe that there are different factors behind these two aspects, then our research design should reflect this and analyze the two separately.

In the recent literature, very few contributions have used an incidence design. Reynal-Querol's (2002) analysis of the interplay between ethnic polarization and political regimes is one of the exceptions. She reports that her results stay the same when she uses an onset specification, which supports the argument of corroborating effects on initiation and duration. One way of testing this argument is to apply a dynamic model of incidence. By introduction a variable measuring last years value on the dependent variable, i.e. whether there was an active conflict the year before, an option becomes available to us. We can interact this variable, often called the lagged dependent variable (LDV), with all the explanatory variables in our equation. If the interaction term between the LDV and the democracy variable is small and insignificant, then the effect of democracy is indeed constant. However, if it is not small and insignificant, then we should reevaluate our design.

Introducing a lagged dependent variable tells us something obvious and important: Wars tend to be self-perpetuating. Thus, the best predictor of conflict in a given year is whether there was conflict in the preceding year. This is often referred to as time dependency, and is a statistical problem we must address. If we depart from the incidence model and go on to analyze onset and duration in different models, the problems of comparisons and time dependency must be rethought as well. How do we compare events to non-events? And how do onsets relate to each other over time? Incidentally, the first solution to these two problems is to think of them as one problem. Beck, Katz, and Tucker (1998), in a seminal paper proposed to reframe the analysis of interstate conflict onsets as an analysis of the duration of interstate peace periods. Thus, instead of asking why the war begun, they asked why the peace period ended. This effectively transformed the comparison of events and non-events to a question of comparing peace periods. They also pointed out that the longer a pair of countries have been peacefully interacting, the more likely they where to continue that state of affairs, thereby addressing the time dependency problem.

Alas, the Beck, Katz, and Tucker (1998) approach work better with interstate wars than with internal conflicts. The problem is that while a pair of countries either are in a state of war or a state of peace, a single country can experience numerous parallel conflicts. Burma, India, and Indonesia are examples of countries where there are independent conflict going on in different parts of the country at the same time. The consequence is that a conflict can break out even if the country is not in a state of peace. Therefore the analysis of peace periods is not necessarily applicable on the study of armed internal conflicts. Several studies have decided to focus exclusively on the transition from peace to war, and thereby excluding conflicts that start in already war-torn societies. The most prominent application of this approach is Collier and Hoeffler's (2004) analysis of economic causes of civil wars.

If we want to include all onsets, and not only those that start out in previously peaceful societies, we are back at studying events, and we are therefore still in need of something to compare these events to. There are presently two approaches to this problem. Fearon and Laitin's (2003) study of the causes of conflicts use a temporal container solution. That is, they define a period of time, in this instance a year, in which they either observe or do not observe a conflict onset. This temporal container is then compared to all the temporal containers that do not include a conflict onset. This includes both those countries that are peaceful and those that are not. Fearon and Laition report that they have put this solution to numerous different tests of time dependence and do not find any significant effect, apart from that an onset one year is very rarely followed by another onset in the same country the next year. While Fearon and Laitin's approach is very simple, they provide evidence that it is just as good as any more complicated solution to their specific problem. This is a good illustration of the fact that the easiest solution can sometimes be the best.

The alternative approach is to analyze conflict onset as an event. Raknerud and Hegre (1997) provided a model that does exactly this. Rather than constructing a temporal container like Fearon and Laitin did, Raknerud and Hegre based their design on a very small temporal unit, the calendar day. If we where to compare all days that did not see an onset of conflict to those that did, we would end up with a very large dataset which would be too large to answer our questions. Raknerud and Hegre proposed to compare the country that experienced a conflict onset with all other countries independent at the time, but only at the day where the onset took place.

Raknerud and Hegre's approach is appealing, as it gives us a good explanation of the comparison group. Furthermore, since it is not based on a temporal container, it allows us to analyze the effect of preceding events. Certain events, such as election can take place in the same year as a conflict onset. If our temporal unit is a year, it is impossible to know what came first of the two events. The calendar-time solution was also originally developed for the study of interstate conflict, but since it is not based on the duration of peace periods, it has successfully been translated into studies of internal conflict by Hegre et al. (2001). The problem of temporal dependence was also considered by Hegre et al. (2001), using a more complex model than Fearon and Laitin.

The duration perspective of conflict is less controversial. When analyzing duration times, we are mostly interested in conflicts that has occurred, and not so much in those that hasn't started. Indeed, in an ideal world, we could just compare average log of duration times with an OLS model between different political regimes. The reason for why this is infeasible is the fact that some conflicts are still ongoing. All we know about these conflicts is that they have lasted for some time, but we do not know the final duration of them. How do we solve this problem? The standard approach for such matters is to rephrase the question from "what makes a conflict endure?" to "what makes a conflict terminate?". The link between these to questions is that the more likely a given conflict is to terminate, the shorter expected duration it will have. Within the latter question, we can analyze the fact that the ongoing conflicts have evaded termination up until the point in time which we observe them. The statistical models applied to these questions are often called event history analysis[1].

Finally, the magnitude of conflicts reflects quantitative differences between conflicts. Some conflicts are large and others are small, but they vary along a continuum. Such differences are best explored by a linear regression model, such as OLS.

Econometric setup

The econometric specifications of onset, incidence, duration and magnitude are different but the results we present are nevertheless comparable, as we focus on the relative differences. The relevant question for relative differences is "How many times more or less of a quantity do we get if we alter our X variable?"

For onset, we use a calendar time Cox model; for incidence we use a Logit model; for duration we use a Weibull regression model; and for magnitude we use a standard OLS model. Since these models and their underlying data structures are different, we also use different set of control variables.

OLS model

Since the linear OLS model is the simplest model, we start here. Our quantity of interest is the magnitude of conflict, measured as the number of fatalities during a calendar year, denoted *M*. We start by taking the natural logarithm of *M*, *ln(M)*. Since political institutions are far from the only factor influencing the magnitude of conflict, using absolute numbers would be deceitful. More people were killed in the Vietnam War than there are inhabitants on Iceland. However, we believe that democracy should have the same relative influence on all societies, i.e. reducing the magnitude of conflict by the same factor. If that saves 100 or 100 000 lives depend on the other characteristics of that conflict. The natural logarithm allows us to do this, as $\ln(x)+\ln(2)=2*x$. That is, a constant increase of the logarithmic scale relates to a doubling of the absolute scale. The OLS specifications of our equation is $\ln(M_{i,t}) = \alpha + \delta \ln(M_{i,t-1}) + \beta X_{it-1} + \gamma Z_i$, where alpha is the constant term, $\ln(M_{t-1})$ is last year's recording of the dependent

[1] See Box-Steffensmeier and Jones (2003) for a very good introduction to these models.

variable, X is a set of variables that vary from year to year, and Z is a set of variables that do not vary from year to year.

The comparative aspect is then the difference between two conflict years, M_1 and M_2, which is given by ln(M_1)- ln(M_2). This is equivalent to the natural logarithm of the ratio $\ln\left(\frac{M_1}{M_2}\right)$, and this ratio is exactly what we are interested in. Let us assume that M_1 and M_2 are similar but for one variable, *D,* in which M_1 is one unit above M_2, and that this is the only variable in the set *X*. How do we interpret this difference? Let us first state the two equations:

$$\ln(M_{1,t}) = \alpha + \delta \ln(M_{1,t-1}) + \beta(D+1)_{t-1} + \gamma Z$$

$$\ln(M_{2,t}) = \alpha + \delta \ln(M_{2,t-1}) + \beta(D)_{t-1} + \gamma Z$$

Since these observations where similar but for that one trait, we can assume they had the same fatality level last year also. The difference between them is given by e^{β} because all other factors cancel each other out. The reasoning is as follows:

$$\ln(M_{1,t}) - \ln(M_{2,t}) = (\alpha + \delta \ln(M_{1,t-1}) + \beta(D+1)_{t-1} + \gamma Z) - (\alpha + \delta \ln(M_{2,t-1}) + \beta D_{t-1} + \gamma Z)$$
$$\ln\left(\frac{M_{1,t}}{M_{2,t}}\right) = \alpha - \alpha + \delta \ln(M_{1,t-1}) - \delta \ln(M_{2,t-1}) + \gamma Z - \gamma Z + \beta(D+1)_{t-1} - \beta D_{t-1}$$
$$\ln\left(\frac{M_{1,t}}{M_{2,t}}\right) = \beta(D+1)_{t-1} - \beta D_{t-1} = \beta D_{t-1} - \beta D_{t-1} + \beta$$
$$\ln\left(\frac{M_{1,t}}{M_{2,t}}\right) = \beta$$
$$\frac{M_{1,t}}{M_{2,t}} = e^{\beta}$$

The ratio, or the relative difference between M_1 and M_2 is given by the anti-logarithm of the coefficient beta, and this is the figure we report in our tables.

Logistic model

Let us continue to the incidence model and logistic regression. The logit regression model assumes that all country-years are under risk of experiencing conflict, but that all we observe is whether conflict is present or not. Our quantity of interest is then the difference in probability of conflict caused by a specific variable. The betting industry has familiarized the term 'odds', which is a measure of probability. The odds, O, favoring war in a given observation is the fraction $\mathrm{O} = \frac{\Pr(war)}{\Pr(peace)} = \frac{\Pr(war)}{1-\Pr(war)}$. When we take the natural logarithm of an odds, we get a *logit*, and this logit can be estimated as a linear equation.

$$L_{i,t} = \ln(\mathrm{O}_{i,t}) = \ln\left(\frac{\Pr(war)_{i,t}}{1-\Pr(war)_{i,t}}\right) = \alpha + \phi war_{i,t-1} + \beta X_{i,t-1} + \gamma Z_i$$

In this equaiton $\phi war_{i,t-1}$ is an indicator of whether there was an active conflict in that country the year before, X are variables that change from year to year (such as level of democracy), and Z are variables that do not change from year to year (such as geographic factors). Again, we are interested in the difference between two observations, $L_1 - L_2$. Since the logits are the natural logarithm of the corresponding odds, this difference is equal to the natural logarithm of O_1 divided by O_2. Let us repeat the math.:

$$L_{1,t} - L_{2,t} = \ln(O_{1,t}) - \ln(O_{2,t})$$
$$\ln(O_{1,t}) - \ln(O_{2,t}) = \left(\alpha + \phi war_{1,t-1} + \beta(D+1)_{t-1} + \gamma Z_1\right) - \left(\alpha + \phi war_{2,t-1} + \beta(D)_{t-1} + \gamma Z_2\right)$$
$$\ln\left(\frac{O_{1,t}}{O_{2,t}}\right) = \alpha - \alpha + \phi war_{1,t-1} - \phi war_{2,t-1} + \gamma Z_1 - \gamma Z_2 + \beta(D+1)_{t-1} - \beta D_{t-1}$$
$$\ln\left(\frac{O_{1,t}}{O_{2,t}}\right) = \beta(D+1)_{t-1} - \beta D_{t-1} = \beta D_{t-1} - \beta D_{t-1} + \beta$$
$$\ln\left(\frac{O_1}{O_2}\right) = \beta$$
$$\Theta = \frac{O_1}{O_2} = e^{\beta}$$

Odds 1 divided by odds 2 is an *odds ratio,* denoted Θ. Since the odds are based on comparisons of the number of war observations with the number of peace observations, the interpretation of an odds ratio is that as the corresponding variable increase with one unit, war is e^{β} times more or less likely. For instance, an odds ratio of 2.00 makes the relevant outcome, in our case incidence of conflict, twice as likely, while an odds ratio of 0.73 makes an outcome less likely. In fact the latter result would make conflict 27% less likely. The effect expressed as a percentage change can be received by subtracting the odds ratio from 1 and multiplying the result with 100%.

Weibull model

The two latter models, onset and duration are slightly more complicated. As we have discussed earlier, the transition from peace to war and back again can be seen as events, and there is a distinct branch of regression techniques available for these problems called survival analysis.

Duration of conflict is analyzed through a survival function, where we focus on the transition from war to peace. The quantity we are interested in is a measure of a conflict's propensity to avoid this transition. The dependent variable can be seen as the natural logarithm of conflict duration, ln*(T)*, but this is difficult to estimate since there are two different versions of *T* observed. Some conflicts have ended, and we can therefore observe the real *T*, but other conflicts are still ongoing, and all we know is that they are still active when our observation ends. However, we can turn the problem upside-down, and analyze each conflict's propensity to experience a transition. All conflict, terminated and active, are at risk of making a transition to peace at all times, but some are more likely than others and it is this difference we want to capture.

If our initial model is $\ln(T_i) = \alpha + \beta X_i$, then we our best guess for the duration of conflict, given the covariates *X* is $\ln\left(E(t_i \mid X)\right) = \alpha + \beta X_i$, which is equivalent to $E(t_i \mid X) = e^{\alpha + \beta X_i}$. The mathematical equivalent of turning a problem upside-down is to multiply with minus one. What we then get is a quantity called the *hazard rate,* denoted $h_i(t)$, and given by the expression $h_i(t \mid X) = e^{-(\alpha + \beta X_i)}$. Contrary to the duration of conflict until it terminates, the hazard rate can be estimated for both terminated and active conflict. The active conflicts are given a status as *censored*, which means that we are unable to observe their true termination date. The quantity we are interested in is the difference in hazard rates between two equal observations apart from a one unit difference in the variable D. As we saw earlier when we investigated the difference between odds rates, the interesting quantity when comparing rates is a ratio, or rate 1 divided by rate 2. In our case a fraction containing two hazard rates gives us a *hazard ratio*, which tells us how much the propensity to experience a transition alters when a variable changes one unit. Using the fact that $e^{A+B} = e^A e^B$, we can solve this fraction.

$$\frac{h_1(t \mid D+1)}{h_2(t \mid D)} = \frac{e^{-(\alpha+\beta(D+1)_i)}}{e^{-(\alpha+\beta D_i)}} = \frac{e^{-\alpha}e^{-\beta(D+1)_i}}{e^{-\alpha}e^{-\beta D_i}} = \frac{e^{-\alpha}e^{-\beta D_i}e^{-\beta}}{e^{-\alpha}e^{-\beta D_i}} = e^{-\beta}$$

Finally we got a quantity that we can interpret. The anti-logarithm of the coefficient, from our first formulation of difference in ln(*T*), multiplied with minus one is the hazard ratio and identifies variable *D*'s influence on a conflicts propensity to be resolved, one way or another. Yet, we are not entirely satisfied, since we would prefer to have a measure of what makes conflict endure. Again, we can turn things upside-down, and the opposite of what makes conflicts endure must be what terminates them. The anti-logarithm of the coefficient, e^{β}, can be interpreted as a *time ratio* and inform us how many times longer or shorter a conflict will be if we increase a variable with one unit.

The example above is a slightly simplified version of the model we use. What we have discussed so far is a situation where a conflicts propensity to terminate is uncorrelated with its age. There are several models than explicitly models this relationship rather than assuming it is constant. We have used a weibull model, in which the hazard rate is multiplied with a term pt^{p-1}, and where t is the age of the conflict and p is a shape parameter determining whether conflicts are more or less likely to terminate as the grow older. Interested readers should consult Box-Steffensmeier and Jones (2004) for a very good introduction to survival analysis.

Calendar time Cox model

An analysis of conflict onset implies a focus on the transition from a state of peace to a state of war. When we discussed this topic earlier in this appendix, we concluded that, for our application, the Raknerud-Hegre (1997) calendar time Cox model was superior to a country-year setup since it allows us to precisely date the sequence of events and is more robust against biases stemming from assumptions being breached. We will briefly present the core logic of the calendar time cox model and show why the coefficients reported from this model can be interpreted in the same manner as odds ratios from logistic regression models.

Our interest in the causes of conflict are both factors that are relatively stable over time, such as political institutions, and factors that are themselves events, such as election and regime changes. In order to focus only on situations where a regime changes prior to the outbreak of conflict, we need daily precision. The country-year model does not give us this precision, but we could opt for a country-day model. This model would keep us busy analysis litterally millions of days where nothing happens. As we will see shortly, these observations do not contribute any information. What we are interested in are those days where a transition to conflict occurs. In order to compare these transitions to observations where transition does not occur, we observe all other countries on that day. It can be shown that an analysis of all countries on all days where one country experience a conflict onset yields exactly the same results as an analysis of each and every country-day, *if* the analysis is based on a Raknerud-Hegre (1997) calendar time cox regression.

We are interested in knowing the risk of war in each independent country given that we know that a conflict started on this day, and we will use the hazard rate as the measure of this risk. The hazard rate, $h(t)$. This rate is the product of the baseline hazard, $a(t)$, and the contribution from the independent variables, X. The exact formulation of the hazard rate is

$h_i(t \mid X) = \alpha(t)\exp\left(\sum_{j=1}^{p} \beta_j X_{ji}(t)\right)$. The fact that *a(t)* is held outside the linear equation is one of the major strengths of this approach. While the logistic model and the weibull model must make assumptions regarding the underlying risk of conflict onsets, the cox model does not. The less assumptions we make, the better we are off, and since the baseline hazard is not part of the estimation, we can use the same interpretation as we did in the previous section:

$$\frac{h_1(t \mid D+1)}{h_2(t \mid D)} = \frac{e^{(\beta(D+1)_i)}}{e^{(\beta D_i)}} = \frac{e^{\beta(D+1)_i}}{e^{\beta D_i}} = \frac{e^{\beta D_i} e^{\beta}}{e^{\beta D_i}} = e^{\beta}$$

The Cox model reports relative risks, while the logistic regression model reports odds ratios. We remember that the odds of a given event is the probability of an event happening divided by the probability of the event not happening. The odds of war in a given country is $\mathrm{O} = \frac{\Pr(war)}{\Pr(peace)} = \frac{\Pr(war)}{1-\Pr(war)}$, and the odds ratio is the ratio of two odds, $\Theta = \frac{O_1}{O_2}$. Relative risk (RR) is also based on a fraction, but, as the name implies, a fraction of risks. In our analysis, risk simply refers to the probability of war, pr(war). If we have two groups, the relative risk between them is the ratio of the first group's risk divided by the second group's risk, $RR = \frac{\Pr(war)_1}{\Pr(war)_2}$. Let us exemplifiy this through a contingency table:

	Democracy		Non-democracy	
Transistion to War	49	0.41%	226	0.85%
No Transistion to War	11 977	99.59%	26 208	99.15%
Total	12 026	100%	26 434	100%

The odd of transition to war for a democracy is

$\mathrm{O}_D = \frac{\Pr(war)}{1-\Pr(war)} = \frac{0.0041}{0.9959} = 0.0041$, and the same odds for non-demcracies is

$\mathrm{O}_{ND} = \frac{\Pr(war)}{1-\Pr(war)} = \frac{0.0085}{0.9915} = 0.0086$. The odds ratio is then

$\Theta = \frac{O_D}{O_{ND}} = \frac{0.0041}{0.0086} = 0.477$. The interpretation of the odds ratio is that democracies are 52,3% ([1-0.477]*100%) less likely of experiencing a conflict onset than non-democracies. What answer would we get if we used relative risk instead?

The risk of transition to war in a democracy is 0.41% and the risk of transition to war in a non-democracy is 0.86%. The relative risk indicator is the fraction of the first divided by the latter, $RR = \frac{\Pr(war)_1}{\Pr(war)_2}$, and this gives us

$RR = \frac{0.0041}{0.0086} = 0.482$. The interpretation of the relative risk ratio is that democracies have 51,8% lower probability of conflict onset than autocracies. As we see, the two indicators give us an almost similar outcome, but this is not always the case. If the probability of a transition to war had been higher, the odds ratio and the relative risk would have differed in size. But, as long as the event in question is sufficently rare, the two ratios have comparable coefficients. We can show why. Let us start with the odds ratio:

$$\Theta = \frac{O_D}{O_{ND}} = \frac{\dfrac{\Pr(war_D)}{1-\Pr(war_D)}}{\dfrac{\Pr(war_{ND})}{1-\Pr(war_D)}} = \frac{\Pr(war_D) \bullet (1-\Pr(war_{ND}))}{\Pr(war_{ND}) \bullet (1-\Pr(war_D))}$$

Since relative risk is given by $RR = \frac{\Pr(war_D)}{\Pr(war_{ND})}$, we can substitute RR into the odds ratio equation:

$$\Theta = \frac{O_D}{O_{ND}} = \frac{\dfrac{\Pr(war_D)}{1-\Pr(war_D)}}{\dfrac{\Pr(war_{ND})}{1-\Pr(war_{ND})}} = \frac{\Pr(war_D)}{\Pr(war_{ND})} \bullet \frac{(1-\Pr(war_{ND}))}{(1-\Pr(war_D))} = RR \bullet \frac{(1-\Pr(war_{ND}))}{(1-\Pr(war_D))}$$

As long as the fraction $\frac{(1-\Pr(war_{ND}))}{(1-\Pr(war_D))}$ is fairly close to 1, the odds ratio and the relative risk will be equal (Agresti, 1990, 14ff).

Hypothesis testing

We use standard statistical techniques for hypothesis testing, with a *t*-test for the OLS model and *z*-tests for the three other models. The theory behind these tests assumes that our sample is a random sample, which is a dubious assumption in our case. Yet, the literature on the causes of conflicts has relied on these tests to differentiate between more and less trustworthy results.

Both the *t* and *z* statistic, as they are reported in the major statistical packages, are testing the probability of observing a coefficient given that the real coefficient, β, equals zero. The less probable this proposition is, the more probable is the alternative, that β is larger or smaller than 0. Since we report the anti-logarithm of β, e^{β}, then our test is a test of whether the coefficient reported differs from the anti-logarithm of 0, which is 1.

Decay Functions

We operationalize all our proximity variables as decay functions. Using time since an event poses a problem, because not all countries have experiencesed all events. In our chapter, two events stand out as particularly problematic: previous conflict and elections. Not all countries have had civil wars in modern time, and not all countries have had elections during our period of analysis, yet we can not exclude these countries from our analysis.

The soultion is to measure the time since an event as proximity to that event. A imidiate proximity is coded with the maximum value of 1, and as the event in question becomes less and less proximate in time, the value of our variable approaches 0. All countries which have not experienced such events are coded as 0, which is equal to an experience infinitly long ago. Formally this can be presented as:

$$N(t) = 2^{\left(\frac{-t}{t_{1/2}}\right)}$$

where $N(t)$ is the proximity variable, t is the time since the event took place, and $t_{1/2}$ is the half-life variable. This latter parameter is of crucial importance. It tells us the rate with which the proximity variable decreases from 1 to 0. A half-life parameter of 1 year imply that the effect from an event is at its strongest right after the event takes place, and that it is 50% of its initial effect after one year. After two years, the effect is 25% of the immediate effect, and after three years it is only 12.5%. In other words, the half-life parameter tells us how long it takes before the effect from an event has been reduced by 50%. The smaller this parameter is, the quicker the effect fades away.

Control Variables

In the multivariate models we include several control variables, but these variables differ somewhat from set to set, both with regard to the variables included and with regard to how they are operationalized. The control variables always included are: average income per capita (logged); total population (logged); ethno-linguistic fractionalization (ELF); ELF squared; oil exporter; and proximity to independence.

For the OLS models of Conflict Magnitude, we include the lag of the dependent variable, effectively the natural logarithm of the dependent variable in order to account for temporal dependence. For the logistic regression models of Conflict Incidence, we also add a temporal lag of the dependent variable in order to remove some temporal dependence. We also add a decay function of the time since last conflict in order to account for more persistent temporal dependence. The Weibull regressions used to analyze conflict duration include the incompatibility and presence of international forces in the conflict in order to remove some conflict specific causes.