

# Bargaining and the Interdependent Stages of Civil War Resolution: Supporting Information Appendix

Michael G. Findley  
Department of Government  
University of Texas at Austin  
mikefindley@austin.utexas.edu

May 19, 2012

## 1 Nested Logit

Unlike nested logit, ordered logit does not capture interdependencies among the possible outcomes.<sup>1</sup> More to the point, ordered logit does not distinguish ordered *sequential* outcomes from ordered outcomes (Johnston & DiNardo 1997, 414). Scholars typically use ordered logit (or ordered probit) on ordered scales for which the beginning and end points do not denote any *time sequence*. In studies of American politics, for example, researchers use ordered logit to scale party identification. The scale may span from “strong Republican” at one extreme to “strong Democrat” at the other. This type of scale does not require that earlier values be reached first. In other words, all respondents are not required to be “strong Republican” first, then “weak Republican”, and so on until they arrive at “strong Democrat.” The scale could just as easily be inverted to begin with strong Democrat and end with strong Republican. The only consequence is a corresponding inversion of the signs on the coefficients.

Ordered logit is problematic for peace process data. Not only is there order to the values of the outcome variable, but there is an implied temporal sequence as well. Groups must first decide to negotiate, then reach an agreement, and finally implement the agreement. Suppose one inverts the order of her scale much like the partisanship example? The result is nonsensical. One cannot assume that implementation must occur prior to an agreement, which must occur prior to a decision to negotiate. Thus, an appropriate statistical technique would account for the selection effects created by the interdependencies. Nested logit, a specific form of “nested dichotomies” (Fox 1997), accounts for such effects.<sup>2</sup>

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<sup>1</sup>Walter (2002) uses ordered logit to test her hypotheses because of the small number of cases. Fortunately, more data are now available that make a nested logit test possible.

<sup>2</sup>This discussion of nested dichotomies draws heavily from, and relies almost exclusively on, Fox (1997).

The nested dichotomies technique is based on the dichotomous logit or probit model but extends to the case of polytomous data that imply a time sequence. Similar to logit or probit, the nested dichotomies technique produces maximum likelihood estimates.<sup>3</sup> Estimating nested dichotomies requires the researcher to produce  $m - 1$  dichotomies from an  $m$ -category set of outcomes. This requires partitioning the entire set of data and then successively partitioning the already partitioned data until only a binary outcome remains. To illustrate, consider the following figure, which comes from Fox (1997).

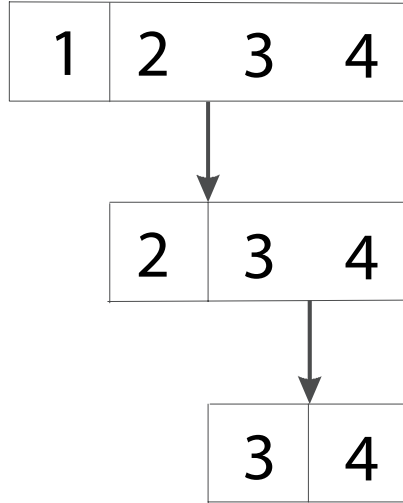


Figure 1: Estimation of Nested Dichotomies: Three dichotomies to reflect the three stages of the peace process.

In the case of civil wars, let (1) represent no decision to negotiate, (2) represent a decision to negotiate, (3) represent that an agreement is reached, and (4) represent a successfully implemented agreement. Then the initial dichotomy  $\{1, 234\}$  represents a decision to negotiate,  $\{2, 34\}$  indicates a negotiated agreement *conditional* on the decision to negotiate, and  $\{3, 4\}$  indicates implementation of an agreement, *conditional* on deciding to negotiate and reaching an agreement. This implies that once the first dichotomy ( $\{1, 234\}$ ) is estimated, all observations of value 1 are dropped from the sample and the next dichotomy ( $\{2, 34\}$ ) is estimated on the remaining cases. This procedure continues until only one dichotomy remains. In this way, the nested dichotomies technique captures the sequential ordering of the process.

Although estimating nested dichotomies explicitly captures *sequence*, it does not capture *timing* per se. To illustrate, if one has access to the *times* in which runners finish a race, then from those times one can establish both the timing of completion and the order (1st, 2nd, 3rd) in which the runners complete the race. If, on the other hand, one only has access to a list of the order in which runners finished, then one cannot infer the actual times of completion. The nested dichotomies approach is similar to the second situation

<sup>3</sup>Furthermore, the models are all statistically independent despite being fitted to data from the same sample (Fox 1997, 473–474).

in which the data structure and estimator explicitly capture sequence or order but not timing.

Fox (1997) notes that the nested dichotomies technique requires the researcher to defend a particular choice of dichotomies. Indeed, I might have partitioned my data differently. I could have, for example, set the initial dichotomy as  $\{12, 34\}$ , and then subsequently partitioned these two halves as  $\{1, 2\}$  and  $\{3, 4\}$ . This alternative is substantively less compelling than the first choice discussed above. This latter division implies that groups in a civil war decide between continuing war and negotiating on the one hand, and agreeing to a settlement or successfully implementing an agreement on the other. Conditional on either of these decisions, they then further narrow down their choices. Thus, in the first case, after deciding either to continue war or deciding to negotiate, the groups would choose either a continuation of war or negotiations as the final outcome. Negotiations could not be followed by an agreement in this formulation, which makes no sense because the purpose of negotiating is to discuss and, perhaps, reach an agreement.

The particular set of dichotomies I constructed for my analysis above ( $\{1, 234\}$ ,  $\{2, 34\}$ , and  $\{3, 4\}$ ) fits closely with the theoretical model and is consistent with the theoretical literature more generally. Namely, assuming each of the stages is reached, they occur in an order that is intuitive: war is followed by negotiations, which is followed by an agreement, which is followed by an implementation period.

The advantage of using nested dichotomies is that this approach explicitly captures the interdependence inherent in progressing from one stage to the next. For example, as academics progress through their careers, typically a full professor must previously have been an assistant and associate professor (Fox 1997). It is mandatory to pass through each of these stages to reach the final one (full professor). Even a selection model, such as Heckman's (1979), does not capture this explicitly. A Heckman model includes stages, but emphasizes finding different sets of covariates that account for one stage and not the other. A Heckman approach applied to the college professor example would emphasize factors, such as publication record, that made some individuals more successful than others. But, importantly, this technique does not *require* that a full professor advance through the stages of assistant and associate professor, though likely these would be good predictors. This stands in contrast to the nested dichotomies approach, which explicitly requires that each stage be reached before the next stage can.

A nested dichotomies approach allows me to estimate the factors that affect a group's decision to move from one stage of the peace process to the next stage: from Stage 1 to Stage 2, Stage 2 to Stage 3, and then from Stage 3 to Stage 4. This approach is crucial because I propose that combatants participate in all three stages of a settlement process and that events throughout the entire process can shape the final outcome.

## 2 Robustness Checks

To check the robustness of the results, I estimate a few additional models with different measures of the key concepts. The following analyses provide further tests of the

predictions of the theoretical model with measures from alternate sources for the number of factions, the capability distribution, and third-party involvement. Given that the state military interventions are not central to the model, I did not include them in the robustness checks. I also drop civil wars that Doyle & Sambanis (2000) flag as possibly not meeting the criteria of a civil war and reestimate the models for the three stages. Table 1 displays the results of three additional regressions for each of the three stages of the analysis.<sup>4</sup>

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<sup>4</sup>Note that each model is now arrayed by column rather than row and I report the coefficient with standard errors immediately below. Variables that are statistically significant at the 0.1 level are in bold. Shaded values indicate the new measure being analyzed in each regression.

Covariate	Stage 1			Stage 2			Stage 3		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Number of Factions	<b>0.282</b> ( <b>0.177</b> )	<b>0.314</b> ( <b>0.144</b> )	<b>0.314</b> ( <b>0.144</b> )		0.041 (0.208)	0.023 (0.195)		<b>-0.525</b> ( <b>0.216</b> )	<b>-0.457</b> ( <b>0.194</b> )
Rebel Strength		<b>0.539</b> ( <b>0.310</b> )	<b>0.625</b> ( <b>0.289</b> )						
Stalemate	<b>2.126</b> ( <b>0.535</b> )	<b>1.847</b> ( <b>0.523</b> )	<b>2.029</b> ( <b>0.489</b> )	0.658 (0.699)	0.488 (0.647)	0.654 (0.646)	<b>-1.388</b> <b>0.638</b>	<b>-1.272</b> <b>0.619</b>	<b>-1.334</b> <b>0.592</b>
Peace Operation	<b>0.747</b> ( <b>0.259</b> )	<b>0.681</b> ( <b>0.249</b> )		<b>-0.331</b> ( <b>0.223</b> )		<b>-0.326</b> ( <b>0.218</b> )	<b>0.642</b> ( <b>0.241</b> )	<b>0.616</b> ( <b>0.285</b> )	<b>0.616</b> ( <b>0.285</b> )
Power Sharing				<b>1.484</b> ( <b>0.466</b> )	<b>1.405</b> ( <b>0.456</b> )	<b>1.464</b> ( <b>0.481</b> )	<b>0.593</b> ( <b>0.245</b> )	<b>0.598</b> ( <b>0.272</b> )	<b>0.550</b> ( <b>0.244</b> )
Security Guarantee				<b>1.860</b> ( <b>1.425</b> )	<b>1.747</b> ( <b>1.352</b> )	<b>1.870</b> ( <b>1.457</b> )	<b>0.462</b> ( <b>0.823</b> )	<b>1.050</b> ( <b>0.896</b> )	<b>0.908</b> ( <b>1.008</b> )
UN Peace Operation					<b>-0.533</b> ( <b>0.670</b> )			<b>1.860</b> ( <b>0.756</b> )	
Symmetry	<b>1.167</b> ( <b>0.448</b> )					<b>0.206</b> ( <b>0.472</b> )			<b>0.898</b> ( <b>0.965</b> )
Number of Factions (D/S)		<b>0.234</b> ( <b>0.133</b> )		<b>-0.029</b> ( <b>0.145</b> )			<b>-0.244</b> ( <b>0.214</b> )		
Peace Enforcement			<b>1.209</b> ( <b>0.928</b> )						
Constant	<b>-4.061</b> ( <b>1.193</b> )	<b>-2.718</b> ( <b>0.911</b> )	<b>-2.743</b> ( <b>0.804</b> )	<b>-0.513</b> ( <b>0.730</b> )	<b>-0.888</b> ( <b>0.841</b> )	<b>-1.117</b> ( <b>1.379</b> )	<b>-0.112</b> ( <b>0.932</b> )	<b>0.806</b> ( <b>0.926</b> )	<b>-1.334</b> ( <b>2.358</b> )
$P > \chi^2$	<0.000	<0.000	<0.000	<0.042	<0.075	<0.033	<0.004	<0.001	<0.052
Pseudo $R^2$	0.350	0.313	0.235	0.349	0.331	0.350	0.250	0.308	0.320

Standard errors in parentheses; bold=  $p < 0.1$ ; shaded region=alternative measures

Table 1: Alternative Specifications for Each Stage of the Analysis

Estimating three additional models for Stage 1 (Models 1–3) shows no change to the directions or statistical significance of the variables. Model 1 incorporates a transformation of the rebel strength measure that more accurately captures parity in the capability distribution. In this case, I “fold” the measure such that values of much stronger and much weaker (5 and 1 respectively) and stronger and weaker (4 and 2 respectively) are identical. In other words, “much stronger” and “much weaker” share a single value of 1, stronger and weaker share a value of 2, and parity assumes a value of 3. This transformed measure more accurately captures the parity/preponderance dimension, and yields a much higher coefficient (1.167 compared to 0.526).<sup>5</sup> Thus the results are even better when incorporating this variable, but I choose to report the rebel strength measure as it does not rely on a transformation.

In Model 2, I use a different measure of the number of factions from the Doyle & Sambanis (2000) data set, and in Model 3, I use a measure of peace enforcement that attempts to capture whether third-parties intervene forcefully during the war to bring about the peace process. In both of these later cases, the results do not change.

The robustness checks for Stage 2 (Models 4–6) are reported in Table 1. In Model 4, it appears that using the Doyle & Sambanis (2000) measure of the number of factions makes the likelihood of reaching an agreement less likely, which is consistent with the direction of the relationship that the theory expects. This measure is not, however, statistically significant. In Model 5, I use a measure of UN peace operations (as opposed to any peace operations), and although the sign on the coefficient is the same, it is not statistically significant. This suggests that non-UN peace operations are even less likely to be successful at getting combatants to reach an agreement than UN peace operations. My theoretical model does not provide an explanation for differences in third-parties, and thus further research disentangling these results would be useful. Finally, the parity measure in Model 6 (explained above) is positive like in Stage 1 but it is not statistically significant, although it is unclear what this result means given that the variable is measured at the outset of the war. None of the other variables changed in the sign on the coefficient or the statistical significance.

In Model 7, when incorporating the alternative measure of the number of actors from Doyle & Sambanis (2000), the sign on the coefficient remains, but now the covariate is not statistically significant. Although I did not report p-values in this table, this covariate has a p-value of 0.102, just missing the 0.1 cutoff. Thus, although there is a small change for this measure, it perhaps only weakens the result slightly (assuming the 0.1 threshold is the relevant cutoff point). In Model 8, I incorporate a UN peace operation measure that does not change any of the results. Finally, the measure of parity in Model 9 yields a positive coefficient, but is not statistically significant. It is likely, however, that the parity measure is not meaningful by this stage given changes throughout the war and peace process.

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<sup>5</sup>To be sure, there are potential problems using such a measure, which is why I use this measure only in the robustness check. First, in order to obtain the measure, I am conducting a transformation of an ordinal variable, which already stretches the limits of good statistical practice. Second, by folding the variable I am making the implicit assumption that a rebel group being “much stronger” is exactly the same as the government being “much stronger.”

Finally, because there is considerable disagreement about how to define civil wars (Sambanis 2004), it is possible that not all of the cases in the dataset reach the criteria of a civil war. In their dataset, Doyle & Sambanis (2000) include a tag for cases that might meet the definition of civil war but are ambiguous. I reestimated each of the three stages dropping the ambiguous cases (3 cases from Stage 1 and 2 cases from Stages 2 and 3), and the results of the analysis are nearly identical. In all stages and for all variables, the direction of the coefficients remained the same. For three covariates the p-values shifted (twice lower, once higher) but all of them continue to be significant at the 0.1 level. Thus, the results appear to be robust even when considering a slightly altered, and stricter set of cases.

### 3 Model Fit

I also estimated ROC curves and the fraction correctly predicted by the models to evaluate the overall model fit. For Stage 1, the ROC curve for the logit regression returned an area of 0.8753, which is a fairly large area, suggesting that the regression has a good fit. The percent classified correctly is 78.45% and, with control variables, the error in classification is reduced by 61.5%. For Stage 2, the ROC curve for the logit regression returned an area of 0.9209, which is a fairly large area, also suggesting an overall good fit. The percent classified correctly is 85.71% and, with control variables, the error in classification is reduced by 79.3%. Finally, for Stage 3, the ROC curve for the logit regression returned an area of 0.8501, also a fairly significant area, suggesting that the regression has a good fit. The percent classified correctly is 72.92% and, with control variables, the error in classification is reduced by 51.8%.

### 4 Coding Rules

Below I describe the sample of civil wars as well as the coding rules for each of the variables in the analyses. The variable names are in bold and are followed by a brief explanation of their source and coding criteria. Some of the variables are drawn from other data sources, and for most measures, I collected additional data when the sets of cases did not overlap perfectly. For the dependent variable, I modified and substantially updated Walter's (2002) data.

#### 4.1 The Set of Civil Wars

The set of civil wars is based on Doyle & Sambanis (2000). They classify a conflict as a civil war if:

1. "the war has caused more than one-thousand battle deaths;
2. the war represented a challenge to the sovereignty of an internationally recognized state;

3. the war occurred within the recognized boundary of that state;
4. the war involved the state as one of the principal combatants;
5. the rebels were able to mount an organized military opposition to the state and to inflict significant casualties on the state” (Doyle & Sambanis 2000, coding notes, 3).

In general, their definition is similar to standard definitions but relaxes a couple of restrictions, such as the requirement that the one-thousand battle deaths occur in each year. In their dataset, there needs to be one-thousand deaths over the course of the conflict. Their article and coding notes provide much more detail about the sample of wars (Doyle & Sambanis 2000).

## 4.2 Coding Rules

**Stages of the Peace Process** are the dependent variables and are based on Walter’s (2002) coding. The measure is an ordered, sequential categorical variable with the following outcomes: 0=no negotiations occurred, 1=negotiations occurred, 2=agreement signed, 3=agreement implemented. For the analysis, these categories are collapsed into three dependent variables for the three-stage estimation of the nested dichotomies. Figure 2 displays the distribution of outcomes based on each stage of the analysis.

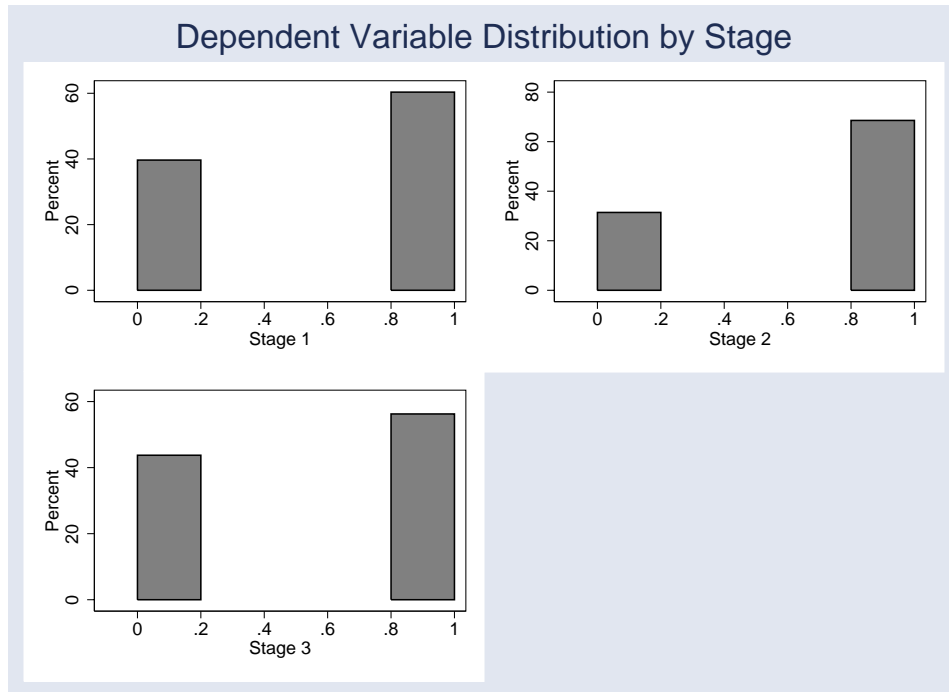


Figure 2: Stages of the Peace Process

Walter (2002, codebook) provides a thorough explanation of how these stages are coded generally. I mostly follow her criteria, except in a couple of respects. First, because it is



difficult and perhaps impossible due to strategic behavior to identify when combatants are negotiating or implementing in good faith, I code any formal negotiations, agreements, or implementation that occur, with the exception of events related to ceasefires, which is consistent with Walter (2002). Second, I did not require that all parties were included in negotiations, agreements, or implementation efforts. In these respects, I deviate from Walter's (2002) coding rules because the rules preclude capturing strategic behavior or the dynamics of multiple parties, which are important to the argument. Third, overly restrictive coding rules might actually bias the results in favor of more cooperation.

**Number of Factions** is a count variable ranging from 2 to 10 that captures the number of actors involved in a civil war. This measure is drawn from Cunningham, Gleditsch & Salehyan (2005). In the robustness checks section, I use the measure of the number of factions from the Doyle & Sambanis (2000) dataset which is also a count variable but ranges from 2 to 11. The robustness results reported below show that the two measures produce similar results. Figure 3 displays the distribution of this variable where the top-left is for Stage 1, the top-right is for Stage 2, and the bottom-left is for Stage 3.

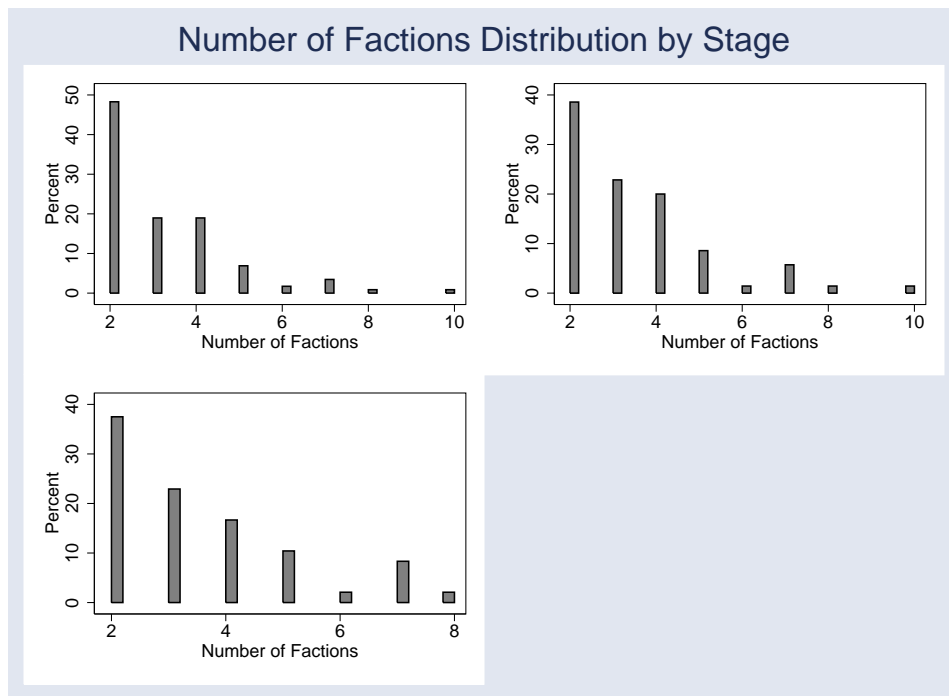


Figure 3: Number of Factions at All Three Stages

**Rebel Strength** is an ordinal measure capturing rebel strength vis-à-vis the government. The measure ranges from 1 to 5 where:

1 = rebels much weaker

2 = rebels weaker

3 = rebels at parity

4 = rebels stronger

5 = rebels much stronger.

This measure is drawn from the Cunningham, Gleditsch & Salehyan (2005) dataset, but because their data are dyadic, I use the coding for the strongest rebel group. Figure 4 displays the distribution of this variable for Stage 1.

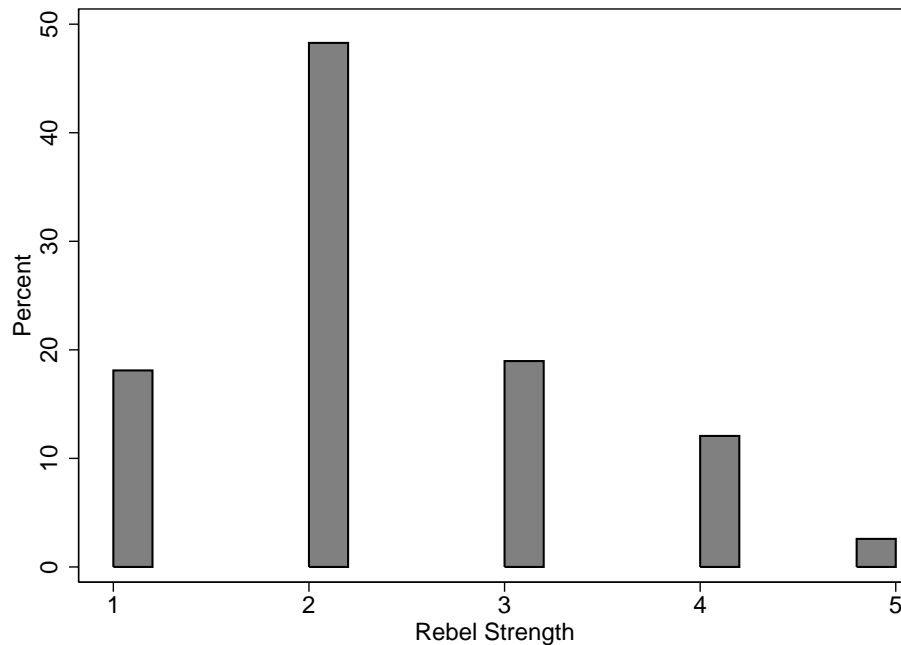


Figure 4: Rebel Strength Distribution in Stage 1

**Stalemate** is a dichotomous variable indicating whether a military stalemate occurred during the civil war. It is drawn from the Mukherjee (2006) dataset. Figure 5 displays the distribution of this variable for Stages 1 and 2.

**Peace Operation** is an ordinal measure capturing the highest level of involvement in a UN or non-UN peace operation. The measure ranges from 0 to 4 where:

0 = no involvement

1 = mediation

2 = observers

3 = peacekeepers

4 = peace enforcement.

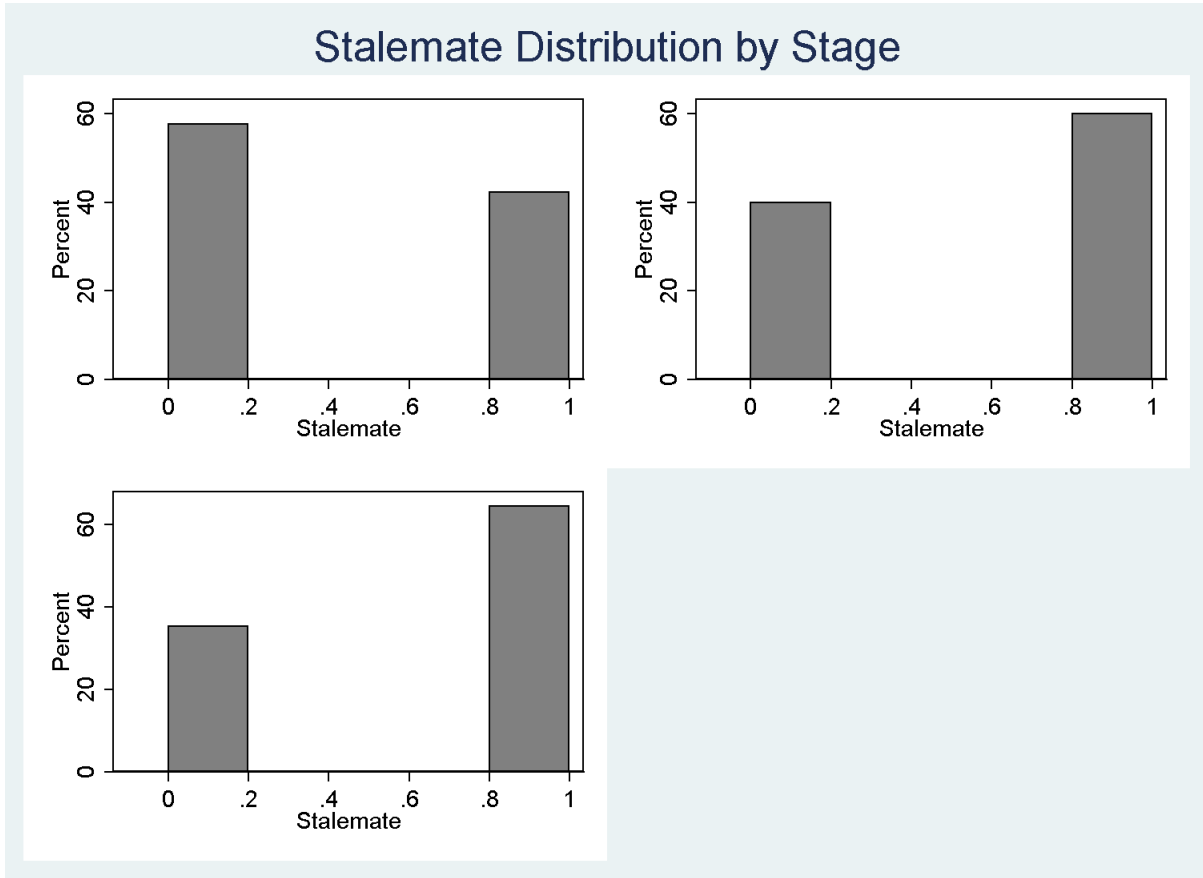


Figure 5: Stalemate Distribution for Stages 1 and 2

This measure is from the Doyle & Sambanis (2000) data set, and Figure 6 shows the distribution of the variable for all 3 stages (the top-left is for Stage 1, the top-right is for Stage 2, and the bottom-left is for Stage 3).

**Power Sharing** is a count variable capturing the number of political, military, and territorial pacts concluded by the parties to a peace agreement. The measure ranges from 0 to 4 and is drawn from the Mukherjee (2006) dataset. Figure 7 displays the distribution of this variable for Stages 2 and 3.

**Security Guarantee** is a dichotomous variable capturing whether a third-party promises to guarantee the terms of an agreement by intervening with troops to ensure that violence does not resume. This measure is based on Walter's (2002) coding rules and is updated in Cunningham (2006). Figure 8 displays the distribution of this variable for Stages 2 and 3.

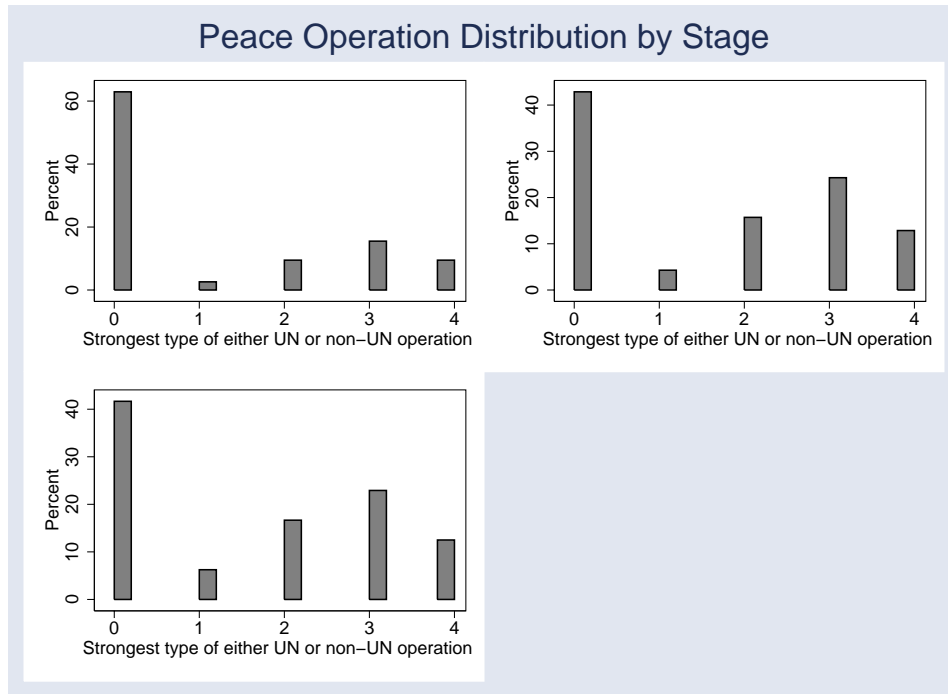


Figure 6: Peace Operations Distribution for Stages 1, 2, and 3

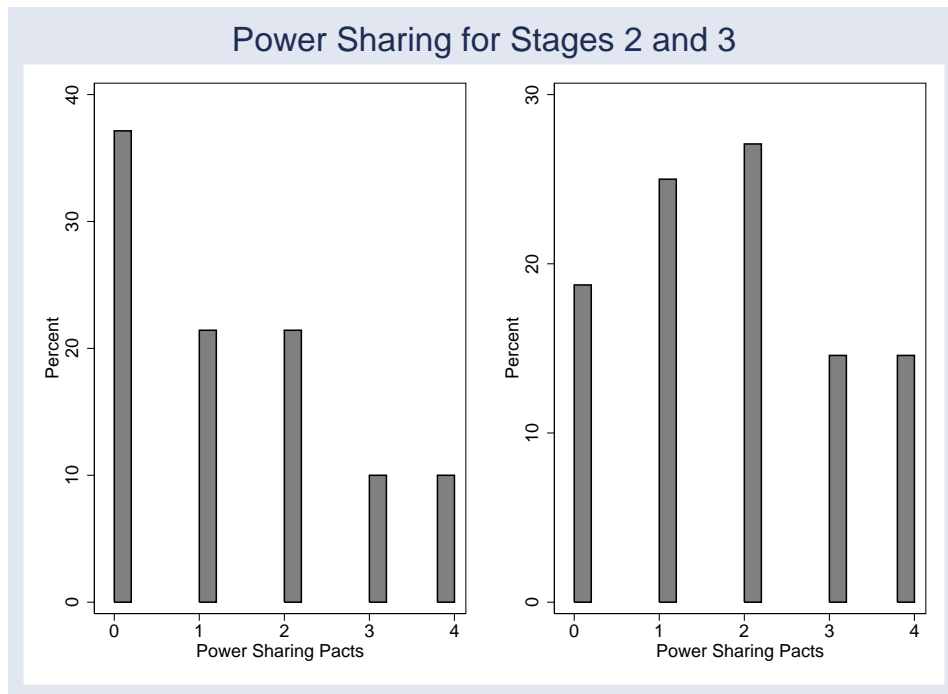


Figure 7: Power Sharing Distribution for Stages 2 and 3

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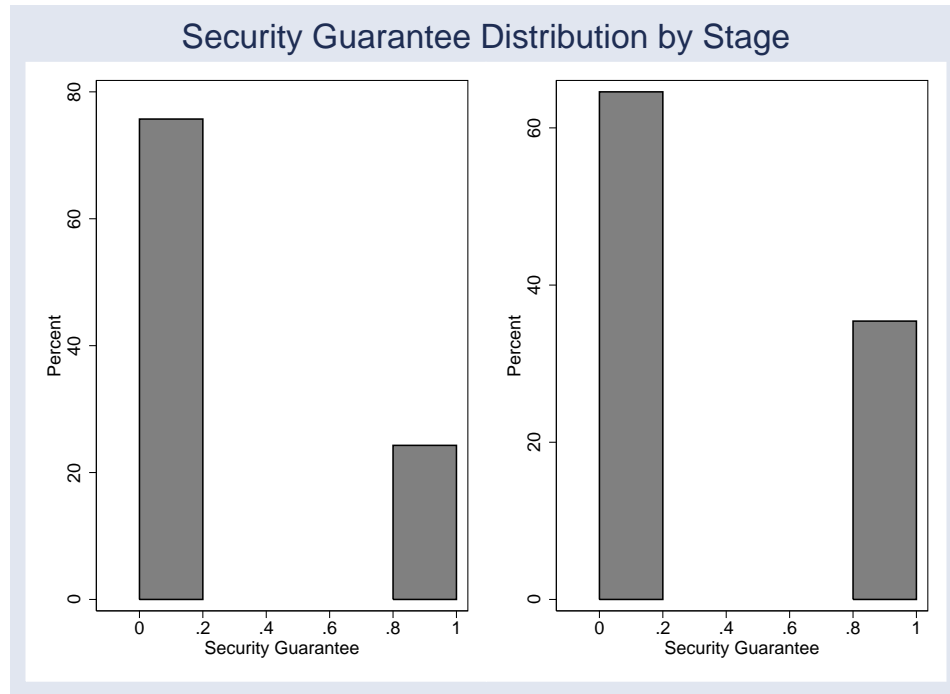


Figure 8: Security Guarantee Distribution for Stages 2 and 3

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