To Intervene or Not to Intervene

A BIASED DECISION

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Alliances are related to the occurrence of conflict. A theoretical model predicts how alliance reliability affects the occurrence of conflict in the international system. Suppose that two nations are at war. The intervention of a third nation into this war affects the likely outcome. Nations prefer to fight wars that they expect to win. Nations are more likely to involve themselves in wars in which they anticipate allied support. Estimates of alliance reliability are obtained and used to demonstrate that nations consider alliance reliability when deciding whether to become involved in conflict. For example, nations with unreliable allies are more likely to surrender if attacked than are nations with reliable allies. Alliance reliability affects the occurrence of war. Unfortunately, whether an alliance is honored is only observable when a war actually occurs. The author discusses the sampling bias that this creates.

When attacked, a nation wants to know whether its allies will come to its aid. A nation is more likely to resist if it anticipates allied support. Alliance reliability affects whether nations decide to resist attacks. In fact, alliance reliability also affects whether attacks occur in the first place. Through this process, alliances affect the occurrence of conflict. Unfortunately, whether an ally honors its commitment can be measured only when a war actually occurs. This article examines the claim that alliance reliability affects the occurrence of conflict. Because alliance reliability is observable only when wars actually occur, estimating reliability prior to the onset of war is problematic. I discuss the consequences of these estimation procedures.

A theoretical model explains the role of alliances in international conflict. The model predicts the relationship between alliance reliability and the occurrence of conflict. To test the model's hypotheses, I estimate alliance

AUTHOR'S NOTE: I gratefully acknowledge the advice of Chris Achen, Bruce Bueno de Mesquita, Fiona McGillivray, Jim Morrow, Bob Parks, Doug Rivers, Randy Siverson, Renee Smith, and several anonymous referees. They should in no way be accountable for my inability to follow their advice.

JOURNAL OF CONFLICT RESOLUTION, Vol. 40 No. 1, March 1996 16-40

reliability using alliance characteristics. The theory suggests that other nations care about the reliability of alliances. Nations that anticipate allied support should a war occur are likely to undertake actions that lead to war. An empirical test shows that nations consider alliance reliability when deciding whether to initiate conflict. The endogeneity between alliance reliability and the occurrence of conflict leads to sampling problems in the estimation of alliance reliability. I discuss the nature and consequences of these sampling biases.

I estimate whether nations honor alliance commitments and support allies who become involved in wars. I refer to this as *alliance reliability*.[1] Nations form alliances in the expectation that if they become involved in a war, their alliance partners will come to their aid. Empirically, one observes that this rarely happens. Only about one nation in four honors its alliance commitments. This result varies with the data set used and the definition of alliances and war (Siverson and King 1980; Sabrosky 1980; Altfeld and Bueno de Mesquita 1979; King 1989; Oren 1990; Kim 1991; Siverson and Tennefoss 1984). However, on the whole, it appears that alliances are unreliable. This is at odds with alliance formation theories. These theories typically assume that alliances are reliable.

If a nation becomes involved in a war, then about one quarter of the time its allies come to its aid.[2] This figure of approximately 25% appears much greater when compared with the probability of a nonallied nation intervening in a conflict. Although nonallied states sometimes intervene to support a nation involved in a war—for example, England and France intervened to support Turkey against Russia in the Crimean War—the probability of this occurring is only a few percent. One can say, then, that an alliance does not guarantee that a nation will intervene to help its ally in the event of a war. However, an alliance makes assistance much more likely than if no alliance exists between the two nations.

Siverson and King (1980), Sabrosky (1980), Altfeld and Bueno de Mesquita (1979), and Kim (1991) estimated the reliability of alliances by observing whether allies intervene on behalf of alliance partners who become involved in a war. Each study is interested in a slightly different question and so uses different data sets and coding decisions. For example, Siverson and

1. Alliance can take numerous forms. In many alliances, a nation does not actually have to intervene to fulfill its commitments. For example, nonaggression pacts require only that a nation not attack its ally. Although it is inaccurate in a strict sense, I use the term *alliance reliability* for convenience.

2. Kim (1991) showed that if one alliance partner intervenes in a conflict, then other alliance partners are also likely to intervene. Typically, either all or none of the alliance partners honor their commitments. Although empirically, allies are likely to make the same decision about whether to intervene, Kim's study cannot identify whether nations prefer to fight together or whether this result is driven by a sample selection bias.

King used the nation as the unit of analysis and asked whether it intervenes in a conflict. Alternatively, Sabrosky considered the alliance as a whole when deciding whether the alliance was honored. There are arguments for and against each classification. I, as do Siverson and King, choose the nation as the unit of analysis.

A THEORETICAL MODEL OF CONFLICT INITIATION

Before going on to estimate the likelihood that a nation intervenes in a conflict, I want to consider a simple model of conflict initiation. To simplify the discussion, consider a three-nation system. Each nation has a role. Nation A is a potential aggressor; it decides whether or not to attack nation B. If attacked, nation B, the target, decides whether to retaliate or acquiesce. If B retaliates, then a state of war exists. Once a war occurs, nation C, the third party, decides whether to intervene. This decision by C, to intervene or not, is the dependent variable under consideration.

Suppose nations B and C have shared interests but that these interests are opposed by nation A. Nation C prefers nation B to be victorious over nation A should a war occur. If nation C intervenes in the war, forming a coalition with B against A, then nation B is more likely to win. As the likelihood of nation C intervening increases, the likelihood of B winning also increases. Nation C faces a tradeoff. By intervening, it improves the probability of its favored side winning, but it also has to pay the cost of fighting.

Because nation B prefers to win, it prefers to fight when nation C will support it. As C becomes more likely to support B, B becomes more likely to retaliate if attacked. Nation A wants to gain concessions from nation B. It prefers to get these concessions without having to fight. Nation A is more likely to attack if it suspects that nation B will surrender. If nation A expects that B will retaliate, then a war is likely to occur if A attacks. Because nation A is more likely to win the war if it fights only nation B, rather than a coalition of B and C, A is more likely to attack when C is unlikely to intervene.

Let the probability that C intervenes be γ, the probability that B retaliates be Π, and the probability that A attacks be α. As the backwards induction arguments above show, both α and Π are dependent on γ. As γ, the probability that C intervenes, increases, Π, the probability that B retaliates, increases. In addition, as γ increases, α, the probability that A attacks, decreases. For brevity, the scope of this article is restricted to this defensive situation. However, for the offensive situation, similar arguments show that the more likely C is to intervene on A's behalf, the more likely A is to attack and the more likely B is to surrender. This offensive scenario has been tested elsewhere (Smith 1995b).

The formation of an alliance increases γ. This makes B more likely to retaliate if attacked. In turn, this makes A less likely to attack. The formation of an alliance affects the behavior of A and B in a predictable manner (Smith 1994, 1995a, 1995b). However, the effect of alliance formation on the occurrence of war is ambiguous. The probability of war occurring is $\alpha\,\Pi$, the product of the probabilities that A attacks and B retaliates. Alliance formation increases Π but reduces α. The aggregate effect of alliance formation is unclear. Indeed, empirical studies have failed to establish the correlation between alliance formation and the onset of war (Singer and Small 1966b; Bueno de Mesquita and Singer 1973; Ostrom and Hoole 1978; Levy 1981; Siverson and Sullivan 1984; King 1989, 222-30; Wayman 1990). Vasquez (1987) summarized these studies in a review of the Correlates of War project: "[A]lliances do not prevent war or promote peace; instead they are associated with war, although they are probably not a cause of war" (p. 119). The simple model above is consistent with these findings; alliances do not cause or prevent war, but they are related to the occurrence of war because they affect the probability of third-party intervention.

A STATISTICAL MODEL OF CONFLICT INITIATION

From the simple theoretical model above, I want to construct an empirical test to estimate the probability that a nation intervenes. Using the logic above, I start by considering nation C's decision to intervene in an ongoing war.

C's decision to intervene:

$$Y_c = 1 \text{ if C intervenes, 0 otherwise,}$$

where

$$Y_c = 1 \text{ if } Y_c^* = X_c\beta_c + e_c = Z_c + e_c \geq 0, \text{ and } Y_c = 0 \text{ if } Y_c^* < 0.$$

X_c is a vector of independent variables that affect C's behavior, β_c is a vector of parameters, and e_c is a stochastic error term. For simplicity, assume that the error terms are distributed normally.[3]

B's decision to retaliate:

$$Y_b = 1 \text{ if B retaliates, 0 otherwise,}$$

3. e_i is normalized to N(0,1) because $Y_i^* = \beta_i X_i + e_i$, where $e_i \sim N(0,\sigma^2)$ is equivalent to $Y_i^*/\sigma = \beta_i X_i/\sigma + e_i/\sigma$.

where

$$Y_b = 1 \text{ if } Y_b^* = X_b\beta_{b,1} + Z_c\beta_{b,2} + e_b = Z_b + e_b \geq 0, \text{ and } Y_b = 0 \text{ if } Y_b^* < 0.$$

X_b is a vector of independent variables that affect B's behavior, Z_c represents C's decision, and e_b is a stochastic error term. B's decision depends on C's likely decision.

A's decision to attack:

$$Y_a = 1 \text{ if A attacks, 0 otherwise,}$$

where

$$Y_a = 1 \text{ if } Y_a^* = X_a\beta_{a,1} + Z_b\beta_{a,2} + Z_c\beta_{a,3} + e_a = Z_a + e_a \geq 0, \text{ and } Y_a = 0 \text{ if } Y_a^* < 0.$$

X_a is a vector of independent variables that affect A's decision, Z_b represents B's decision to retaliate, Z_c represents C's decision to intervene, and e_a is a stochastic error term.

This system of three equations is recursive. B's decision whether to retaliate depends on C's decision to intervene, and A's decision whether to attack depends on both B's and C's decisions. Given estimates of C's decision, B's decision could be estimated. In turn, A's decision can be estimated using estimates of B's and C's decisions. Unfortunately, consistently estimating C's decision to intervene is difficult. Whether one observes C's decision depends on whether A attacks and B retaliates. However, the theory above suggests that A's and B's decisions are conditional on C's decision.

ESTIMATING ALLIANCE RELIABILITY

In this section, I discuss the estimation of C's decision to intervene. Given the independent variables X_a, X_b, and X_c, the probability of a multilateral war, a war in which nation C intervenes, is the probability that $Y_a^* \geq 0$, $Y_b^* \geq 0$, and $Y_c^* \geq 0$. Prob.(multilateral war) = Prob.($e_a < Z_a$, $e_b < Z_b$, $e_c < Z_c$). This probability is given by the cumulative trivariate normal distribution, $F(e_a,e_b,e_c,\Sigma)$, where Σ is the covariance matrix of e_a, e_b, and e_c.

$$F(e_a,e_b,e_c,\Sigma) = \int_{-\infty}^{Z_a}\int_{-\infty}^{Z_b}\int_{-\infty}^{Z_c} \frac{1}{\sqrt{2\pi\,|\,\Sigma\,|}} \exp - \frac{e'\Sigma^{-1}e}{2}\, de_a de_b de_c, \text{ where } e' = (e_a,e_b,e_c).$$

The probability of a bilateral war, a war in which nation C does not intervene, is the probability that $Y_a^* \geq 0$, $Y_b^* \geq 0$, and $Y_c^* < 0$. Prob.(bilateral war) = Prob.($Y_a^* \geq 0$, $Y_b^* \geq 0$) – F(e_a,e_b,e_c,Σ). Prob.($Y_a^* \geq 0$, $Y_b^* \geq 0$) is given by a cumulative bivariate normal distribution. The probability of other events can be calculated similarly.

In principle, this model can be estimated by maximum likelihood (Dubin and Rivers 1989). Unfortunately, the likelihood function does not converge. Heckman (1976, 1979) developed a two-step process to correct for sampling effects. The first step estimates the probability of being selected into the sample. These results are used to correct for the sampling effect when estimating the equation under investigation. Unfortunately, the Heckman procedure is designed for a continuous dependent variable. It is inappropriate for evaluating the decision to intervene in an ongoing war. In the appendix, I discuss the Heckman two-step procedure. I also estimate the model with a Heckman procedure. Unfortunately, these estimates are inconsistent. However, they do lend support to the theoretic and empirical arguments made in the main text.

Lacking standard procedures to estimate alliance reliability, I devised an indirect test of the theory's predictions. The test, which is outlined in the following section, shows that nations condition their behavior on the behavior of other nations. For example, the test reveals that the reliability of an alliance affects B's decision to retaliate if attacked. This result is consistent with the theory outlined above and questions the appropriateness of estimating alliance reliability using probit analysis.

A TEST OF WHETHER ALLIANCE RELIABILITY AFFECTS THE OCCURRENCE OF WAR

In this section, I outline a test to decide whether nations condition their behavior on the expected behavior of other nations. To avoid complication, I consider only B's and C's decisions. Thus the following derivation is restricted to events in which nation A has attacked. However, the analysis could be extended to consider A's decision.

The test asks whether B conditions its decision to retaliate on the likelihood that C will intervene. The null hypothesis is that B's decision is independent of C's decision. There is a vector of independent variables, X_c, that affect C's decision to intervene. If the null hypothesis is true, then B's decision does not depend on X_c. Therefore, the distribution of X_c is similar whether or not B retaliates. If the null hypothesis is false and B's decision depends on C's decision, then the distribution of X_c differs between events. I compare the distribution of X_c when B retaliates with the distribution of X_c

when B acquiesces. If these distributions are different, then I reject the null hypothesis that B's decision is independent of C's decision.

This next section shows why the distribution of X_c is constant across different portions of the sample if the null hypothesis is true.

From the model above,

$$Y_c^* = X_c\beta_c + e_c, \text{ and}$$
$$Y_b^* = X_b\beta_{b,1} + (X_c\beta_c)\beta_{b,2} + e_b,$$

where e_c and e_b are distributed N(0,1) with correlation ρ. Let X_c be distributed $g(X_c)$. Let [W|Q] represent the distribution of variable W conditional on another variable Q.

The probability of observing Y_b^*, Y_c^*, and X_c given X_b is

$$p(Y_b^*,Y_c^*,X_c) = p(Y_b^*,Y_c^*,X_c|X_b) = [Y_b^*|Y_c^*,X_c][Y_c^*|X_c]g(X_c) = [X_c|Y_b^*,Y_c^*][Y_b^*,Y_c^*] = [X_c|Y_b^*,Y_c^*][Y_b^*|Y_c^*][Y_c^*],$$

where

$$[Y_c^*] = \int_{X_c} [Y_c^*|X_c]g(X_c)dX_c \text{ and}$$
$$[Y_b^*|Y_c^*] = \int_{X_c} [Y_b^*|Y_c^*,X_c]g(X_c)dX_c.$$

Rearranging this expression yields

$$[X_c|Y_b^*,Y_c^*] = \frac{[Y_b^* \mid Y_c, X_c]\ [Y_c^* \mid X_c]\ g(X_c)}{[Y_b^* \mid Y_c^*]\ [Y_c^*]}.$$

Integrating over Y_c^* yields

$$[X_c|Y_b^*] = \int_{-\infty}^{+\infty} [X_c|Y_b^*,Y_c^*][Y_c^*]dY_c^* =$$
$$\int_{-\infty}^{+\infty} \frac{[Y_b^* \mid Y_c^*, X_c]\ [Y_c^* \mid X_c]\ g(X_c)}{[Y_b^* \mid Y_c^*]} dY_c^*.$$

Given that e_c and e_b are distributed normally, the conditional distributions of Y_b^* and Y_c^* are also distributed normally.

$$[Y_b^*|Y_c^*,X_c] = \frac{1}{\sqrt{2\Pi}\,(1-\rho^2)} \exp - \frac{(Y_b^* - (X_b\,\beta_{b,1} + Z_c\beta_{b,2} + \rho\,(Z_c\beta_{b,2} - Y_c^*)))^2}{2\,(1-\rho^2)},$$

and

$$[Y_c^*|X_c] = \frac{1}{\sqrt{2\Pi}} \exp - \frac{(Y_c^* - X_c^* \beta_c)^2}{2}.$$

If $\rho = 0$ and $\beta_{b,2} = 0$, then $[Y_b^*|Y_c^*,X_c] = \frac{1}{\sqrt{2\Pi}} \exp - \frac{(Y_b^* - (X_b \beta_{b,1}))^2}{2}$. Thus $[X_c|Y_b^*]$ reduces to $g(X_c)$. However, if $\rho \neq 0$ or $\beta_{b,2} \neq 0$, then $[X_c|Y_b^*]$ does not reduces to $g(X_c)$. In this case, $\frac{[Y_b^* \mid Y_c^*, X_c]\ [Y_c^* \mid X_c]}{[Y_b^* \mid Y_c^*]}$ is not independent of X_c. Thus, if either $\rho \neq 0$ or $\beta_{b,2} \neq 0$, then $[X_c|Y_b^*] \neq g(X_c)$. This property forms the basis of the test.

If nation B's decision to retaliate is independent of C's decision to intervene, then $\rho = 0$ and $\beta_{b,2} = 0$. Thus $[X_c|Y_b^* \geq 0] = [X_c|Y_b^* < 0] = g(X_c)$. However, if either $\rho \neq 0$ or $\beta_{b,2} \neq 0$, then $[X_c|Y_b^* \geq 0] \neq [X_c|Y_b^* < 0] \neq g(X_c)$. I use this property to test whether B's decision to retaliate is independent of alliance reliability.

The null hypothesis is that B's decision is not dependent on alliance reliability: $\rho = 0$ and $\beta_{b,2} = 0$. This implies that $[X_c\beta\hat{}_c|\text{War}] = [X_c\beta\hat{}_c|\text{B acquiesces}]$, where $\beta\hat{}_c$ is an estimate of β_c. I test this null hypothesis against the alternative hypothesis that either $\rho \neq 0$ or $\beta_{b,2} \neq 0$. The alternative hypothesis implies that $[X_c\beta\hat{}_c|\text{War}] \neq [X_c\beta\hat{}_c|\text{B acquiesces}]$. Under the null hypothesis, the distribution of the latent variable Y_c^* is identical in all portions of the sample. Under the alternative hypothesis, the distribution of the latent variable Y_c^* varies in different portions of the samples.[4]

In terms of a practical test, I estimate alliance reliability in those events that result in war using probit analysis. Using the parameter estimate, $\beta\hat{}_c$, I predict the reliability of alliances in all events, not just those that end in war. Under the null hypothesis, the distribution of predicted alliance reliability is constant across the sample. This can be tested by comparing the expected reliability of alliances across different portions of the sample. For example, I compare $E[\Phi(X_c\beta\hat{}_c|\text{War})]$ against $E[\Phi(X_c\beta\hat{}_c|\text{B acquiesces})]$.[5] A *t* test can be used to test whether the differences in the means are statistically significant.

WHAT DOES REJECTING THE NULL HYPOTHESIS MEAN?

If the null hypothesis is rejected, then the distribution of alliance reliability varies across different sections of the sample. Substantively, this means that nations consider the reliability of alliances before deciding to attack or before

4. I look at $X_c\beta_c\hat{}$ rather than X_c because of its substantive interpretation.

5. In the case of the ordered probit analysis, $E(X_c\beta_c)$ is compared across sections of the sample.

deciding to retaliate. For example, when nation B decides whether to resist an attack, it considers the probability that its alliance partner, C, will intervene. Rejecting the null hypothesis supports the theoretical prediction that alliance reliability is related to the occurrence of conflict.

Suppose nation B considers the reliability of its alliance with nation C before retaliating. This has serious consequences in terms of estimating alliance reliability by observing only events that end in war. Suppose, as in the theoretical model above, that nation B estimates γ, the probability that C will intervene, before deciding whether to retaliate. When estimating C's decision, nation B uses information that is unavailable to us as researchers. For example, diplomatic interactions between B and C are important in B forming beliefs about C's willingness to fight. Unfortunately, such information is difficult to obtain and difficult to quantify. As researchers, we consign the effects of these diplomatic interactions to the error term.

When estimating the likelihood that C intervenes, nation B uses both the information available to us as researchers and the information that it obtained through diplomatic interactions. Using information generally available, nation B can estimate the likelihood of C intervening. Call this estimate $\gamma^\wedge_{general}$. However, nation B has additional information obtained through diplomatic interactions. This information enables B to estimate better the likelihood of C intervening. Call this estimate $\gamma^\wedge_{private}$. Suppose that as a result of diplomatic interactions, nation B expects that nation C is more likely to intervene than is generally thought: $\gamma^\wedge_{private} > \gamma^\wedge_{general}$. If attacked, nation B is likely to retaliate because it expects its ally to intervene. As a result of diplomatic information, nation B knew that e_c had a large positive component. This makes B more likely to retaliate, which is observed as a positive component to its error term, e_b. Therefore, e_c and e_b are positively correlated. Alternatively, if nation B suspects that nation C will remain neutral, then it is likely to acquiesce. Both e_c and e_b are negative.

Rejecting the null hypothesis means that B conditions its decision on alliance reliability. Strictly speaking, this implies that either $\rho \neq 0$ or $\beta_{b,2} \neq 0$. It is possible that only $\beta_{b,2} \neq 0$. Unfortunately, this is unlikely. As the discussion in the previous paragraph outlined, B is likely to estimate alliance reliability using factors that we as researchers do not have systematic data on. Thus, if B conditions its decision on alliance reliability, then it is probable that the errors between C's decision and B's decision are correlated.

Correlation between errors results in biased estimators. There are numerous sources that formally derive the effects of sample bias on estimators (Greene 1990, 715-51; Heckman 1976, 1979; Achen 1986; Little and Rubin 1987; Maddala 1983; Dubin and Rivers 1989). To avoid duplication, this article sketches only the intuition. If B retaliates, then $Y_b^* \geq 0$. This implies that $e_b \geq -Z_b$. If e_c and e_b are distributed bivariate normal with correlation ρ, then $E[e_c|Y_b^* \geq 0] = \rho\lambda(Z_b)$, where $\lambda(Z_b) = \phi(Z_b)/\Phi(Z_b)$, which is commonly referred to as the inverse of Mill's ratio. This implies that Y_c^* is not distributed $N(X_c\beta_c,1)$. Y_c^* is actually distributed $N(X_c\beta_c + \rho\lambda(z_b), (1 - \rho^2\delta(Z_b))$, where $\delta(Z_b) = \lambda(Z_b)(\lambda(Z_b) - Z_b)$. The probit analysis assumes that errors are distributed N(0,1). This is not the case if nations A and B condition their decisions on alliance reliability.

Sample bias typically reduces the magnitude of the coefficients (Achen 1986). If β is the true underlying parameter and β^ the estimated value of the coefficient without correcting for sample bias, then $|\beta| > |\beta\hat{}|$. The true effect of an independent variable on a dependent variable is underrepresented as a result of sampling. If sampling occurs, then the impact of an independent variable on alliance reliability is underrepresented.

EMPIRICAL ANALYSIS

In this section, I estimate alliance reliability using the set of events that result in war. These parameter estimates are used to predict alliance reliability for all events. The average alliance reliability varies across different portions of the sample. These differences are statistically significant and reject the null hypothesis that alliance reliability does not affect the decisions of other nations.

THE DATA

The alliance data used were taken from Singer and Small (1966a, 1969).[6] The events data are taken from Bueno de Mesquita and Lalman (1992). I used Doyle's (1986) definition of democratic nations.

THE DEPENDENT VARIABLE

The event data are composed of European wars and crises from 1815. Events have been rearranged into dyadic pairs of nations. The first nation, A, is from the initiator's side. The second nation, B, is from the target's side. Each nation has a violence score associated with the level of violence it expressed toward the other nation in a particular year. The scores range from 0 to 5. A score of 0 represents no violent behavior or threat of violent behavior toward the other nation. A nation's score increases as it behaves more violently toward the other nation. A score of 4 or 5 represents the actual use of military force.

6. Randy Siverson provided me with additional alliance data, for which I thank him.

TABLE 1
Definition of Events

Event	*Conditions*[a]	*Explanation*
War	$v_a > 3$ and $v_b > 3$	War occurs
Big war (Bigwar)	$v_a = 5$ and $v_b = 5$	War occurs involving at least 1,000 battle fatalities
Acquiescence (ACQ)	$v_a > 3$ and $v_b < 4$	A attacks B, who surrenders
Status quo (SQ)	$v_a < 4$ and $v_b < 4$	No military force is used by either side, although threats may have been made

a. v_a = violence score for nation A (initiator); v_b = violence score for nation B (target); violence scores could range from 0 (no violent behavior or threat of violent behavior) to 5 (use of military force).

The data set contains cases of wars, cases of acquiescence, and cases of the status quo. Given the violence scores, I divide the data into different portions. Let v_a be A's score and v_b be B's score. My definitions of events are given in Table 1.

To construct the intervention decision, I consider the level of violence, v_c, that a third-party nation displays. For each dyad of nations, I consider the actions of each possible third party. Suppose the event that generates the dyadic relationships is a war between A and a coalition of B and C and that each nation has a violence score of 5. When considering the dyadic pair, A and B, I code nation C's intervention decision as $int_b = 5$. B can also be coded as intervening in a war between A and C if the dyadic pair A and C is considered. Because of this ambiguity, I consider two different coding procedures. I consider every possible case of intervention; if two nations fought alongside each other in a war, then both are coded as having intervened on behalf of each other. Clearly, this codes some cases of war initiation as intervention. To overcome these problems, I construct an alternative data set in which I use date order of war entry as a basis for dropping those events that are wars between A and C.[7] The analyses are similar whichever data set is chosen. I present the results obtained using the latter data set. A comparison of analyses obtained using different coding decisions is contained in the appendix. I regard the similarity of these analyses as a test of robustness. The results are not dependent on the coding decisions.

7. Suppose the event I care about is a war between A and a coalition of B and C. This produces two dyads, AB and AC. In the first data set, I consider whether C intervenes in the war between A and B and whether B intervenes in the war between A and C. If nations A and B started the war and if C joined the fight later, then this coding mixes up war initiation and intervention. A second coding decision is used that considers the event as only C intervening in a war between A and B.

TABLE 2
Definition of the Dependent Variable

Dependent Variable	*Alliance*	*Conditions*[a]
Hon	BC	1 if $int_b \geq 4$, 0 otherwise
Hon3	BC	1 if $int_b \geq 4$, –1 if $int_a \geq 4$ and $int_b < 4$, and 0 otherwise

a. int_a = the level of violence that the third party uses in support of nation A; int_b = the level of violence that the third party uses in support of nation B.

When a war occurs, there are three possible outcomes: a nation can fight alongside its ally (Hon3 = 1), remain neutral (Hon3 = 0), or fight against its ally (Hon3 = –1). For convenience, I often collapse the latter two categories into one: if a nation fights alongside its ally, then Hon = 1; otherwise, Hon = 0. The coding decisions are summarized in Table 2.[8]

INDEPENDENT VARIABLES

The age of an alliance affects its reliability; TIME = log(date of war – date of alliance formation + 1). Alliances created for one purpose are less likely to be reliable in other circumstances. As alliances become older, the situations in which nations find themselves are less likely to be those for which the alliance was designed. As alliances age, they become less reliable. Those alliances that form immediately before a war should be the most reliable because they were formed with the prospect that they would be immediately used. These alliances are coded as IMMED = 1.[9] An alternative hypothesis is that alliances become institutionalized over time. If this occurs, then alliances become more reliable over time because the cost of breaking the alliance rises. The institutionalization of alliances is likely to lead to additional ties between allies. If a new alliance forms that supersedes an existing one, then EXIST is coded as 1; otherwise EXIST is coded as 0. As alliances become institutionalized, nations adopt more common issues. This effect is captured by the next independent variable. If B and C have an alliance, then DELTA = $(U_{bc}^{w} - U_{ac}^{w}) - (U_{bc}^{f} - U_{ac}^{f})$, where U_{bc}^{w} = C's utility for the policies of B at the time of war and U_{ac}^{f} = C's utility for the policies of A at the time of alliance formation, and so forth. The utility estimates are based on alliance

8. In Smith (1995b), alternative dependent variables are constructed to reflect higher and lower levels of commitment. The null hypothesis is also rejected in these analyses.

9. The Singer and Small (1966a, 1969) alliance data exclude alliances that formed within one month of a war. Using alliance data supplied by Randy Siverson, I include these immediate alliances and code them as IMMED = 1.

similarities as described by Bueno de Mesquita (1981).[10] If DELTA is positive, the allied states have become friendlier since alliance formation occurred relative to their relationship with the enemy. As DELTA increases, either nations B and C adopt closer policy positions, and hence have greater utility for each other's position, or nation A has moved its policies away from those of nation C. In either case, nation C is closer to nation B compared with nation A, in utility terms, than it was at the time it formed the alliance. Increased friendliness translates into an increased likelihood that the alliance will be honored.

Nations that share policy interests may support each other in the event of conflict whether or not they have formal alliance commitments. To control for this effect, the expected utility (EU) measures developed by Altfeld and Bueno de Mesquita (1979) are included as controls.[11]

As the costs of making and breaking alliances increase, the alliances that form are more reliable. The alliance data are grouped into three categories: (1) mutual defense pacts, (2) nonaggression pacts, and (3) ententes (Singer and Small 1966a, 1969). Mutual defense pacts represent a higher level of commitment than nonaggression pacts. In turn, nonaggression pacts represent higher levels of commitment than ententes. Previous studies (Sabrosky 1980; Siverson and King 1980) have suggested that the probability of intervention is a curvilinear relationship, being highest for defense pacts and lowest for nonaggression pacts. These results are possibly due to the temporal distribution of alliance types. Nonaggression pacts were predominately and almost exclusively formed during the years between the two world wars. Given the common belief that overly tight alliance rigidities led to World War I, it is plausible to suppose that domestic and reputational costs of alliance failure were lower during the interwar years. For this reason, I divide the alliances into discrete classes rather than use a trichotomous variable. NONAG and ENTENTE indicate nonaggression pacts and ententes, respectively.

Democratic states (DEMO = 1) face higher domestic costs for failing to honor alliance commitments. This means that democratic states should be

10. Bueno de Mesquita's (1981) utility measures are based on a nation's alliance portfolio, using the assumption that a nation allies with nations that have similar foreign policy preferences. That these measures are based on alliances creates endogeneity problems. Despite these problems, I continue to use these measures because of the lack of alternatives that cover a large enough temporal or spatial domain to be useful. Using the realist assumption (Snyder and Diesing 1977), the cost of breaking alliances is reputational. Failing to honor an alliance with an ally with whom one has a high utility measure will be very reputationally costly because of the high number of shared allies. Thus alliance portfolio measures can also be thought of as a measure of costs.

11. $EU = (U_{bc} - U_{ac}) * (((cap_b + cap_c)/(cap_a + cap_b + cap_c)) - (cap_b/(cap_a + cap_b)))$, where EU is the expected utility for C of intervening on behalf of its ally, cap_i is the capability of nation i (Singer, Bremmer, and Stuckey 1972), and U_{ij} are expected utility measures (Bueno de Mesquita 1981).

more reliable alliance partners. As states become more powerful and hence more important in determining the outcome of war, the costs of alliance failure increase. Powerful states face large costs for abandoning their allies. Morrow (1991) stated that nations form alliances with nations weaker than themselves to gain policy concessions rather than security. Weaker states gain security from powerful allies in return for policy concessions. The marginal effect of a weak ally on the outcome of a war is low, and so nations are less disappointed if weak allies do not intervene. IMPT captures this effect. IMPT = $cap_c/\log(d_{bc})$, where cap_c is the capability of the ally contemplating intervention and $\log(d_{bc})$ represents the natural logarithm of the distance (in nautical miles) between nation C and its ally B.[12] Finally, BOTH is coded as 1 if a nation is allied to nations on both sides of the conflict.

EMPIRICAL RESULTS

The decision to intervene in a war is estimated using probit analysis. The results are shown in Table 3. The results are similar to those obtained in previous studies. The effect of the independent variables on alliance reliability is as predicted.

THE NULL HYPOTHESIS

The null hypothesis is that nations A and B do not condition their behavior on alliance reliability. If the null hypothesis is true, then the distribution of the independent variables, X_c, should be identical in all portions of the sample. Using the parameter estimates from model 3, I calculate the expected reliability of alliances in all portions of the sample. These are shown in Table 4. The value h(BC) is the predicted probability that nation C will intervene if a war occurs. Table 4 summarizes the predicted values for different parts of the sample. For example, h(BC|Bigwar) is the estimate of alliance reliability for those events in the sample that ended in a large-scale fight.

Comparing the average reliability of alliances for cases of war and cases of acquiescence, it appears that on average, alliances are 7% more reliable if nation B retaliates when attacked. This does not mean that alliances are more reliable as a result of B retaliating; instead, B is more likely to retaliate when alliances are reliable. Conditional on being attacked, nation B's retaliation is more likely when B has a reliable ally.

If the null hypothesis is true, then the distribution of independent variables should be similar across all portions of the sample. A *t* test determines whether

12. The definition of distance between states is taken from Bueno de Mesquita (1981).

TABLE 3
Probit Analysis of the Decision to Intervene

	Model 1	*Model 2*	*Model 3*	*Model 4*
Dependent variable	Hon	Hon	Hon	Hon
Independent variable				
CONS	–1.406**	–1.256**	–0.9720	–0.599
	(0.3419)	(0.3536)	(0.2916)	(0.441)
TIME	–0.0203	–0.0428	–0.0990	–0.3576
	(0.253)	(0.2560)	(0.2518)	(0.290)
DELTA	0.8441**	0.7581*	0.6698*	0.6251*
	(0.3496)	(0.3474)	(0.3357)	(0.347)
EU	0.586	1.412	2.034*	1.182
	(1.1574)	(1.309)	(1.0525)	(1.311)
ENTENTE	–2.013*	–1.710	–1.529	–1.951*
	(1.055)	(1.063)	(1.044)	(1.074)
NONAG	–2.214**	–2.239**	–1.647*	–2.659**
	(0.8206)	(0.8576)	(0.7474)	(0.8924)
IMPT	41.738	43.771		50.83*
	(25.519)	(27.035)		(27.99)
BOTH	0.2396	0.2531		0.1211
	(0.2968)	(0.2982)		(0.304)
DEMO		–1.484**	–1.487	–1.741*
		(0.5209)	(0.5224)	(0.541)
IMMED				–0.975
				(0.6498)
EXIST				–0.6622*
				(0.3453)
n	366	366	366	366
χ^2	26.64	37.59	34.19	43.03

NOTE: Standard errors are in parentheses.
$*p < .05$. $**p < .01$.

TABLE 4
Predicted Values of Alliance Reliability, h(BC|),
for Model 3 across Different Portions of the Sample

Predicted Alliance Reliability	*Mean*	n	SD	*Minimum*	*Maximum*
h(BC|Bigwar)	.236	156	.136	.00986	.653
h(BC|War)	.213	366	.119	.00986	.652
h(BC)	.181	1,772	.128	.00614	.747
h(BC|SQ)	.181	975	.135	.00614	.747
h(BC|ACQ)	.143	355	.114	.00856	.672

TABLE 5
t Test That Different Portions of the Sample Have the Same Expected Value of Alliance Reliability for Model 5

	h(BC|War)	*h(BC)*	*h(BC|SQ)*	*h(BC|ACQ)*
h(BC|Bigwar)	1.93	5.08**	4.68**	7.96**
	(181)	(1,926)	(1,129)	(509)
h(BC|War)		4.35**	3.94**	7.99**
		(2,136)	(1,339)	(719)
h(BC)			0.01	5.18**
			(2,745)	(2,125)
h(BC|SQ)				4.70**
				(1,328)

NOTE: Degrees of freedom are in parentheses.
**$p < .01$.

TABLE 6
Ordered Probit Analysis of the Decision to Intervene

	Model 5	*Model 6*	*Model 7*	*Model 8*
Dependent variable	Hon3	Hon3	Hon3	Hon3 (big wars only)
Independent variable				
TIME	–0.260*	–0.256	–0.0355	–0.078
	(0.203)	(0.273)	(0.241)	(0.386)
DELTA	1.702**	0.448	0.498	0.236
	(0.476)	(0.345)	(0.348)	(0.378)
EU	–0.114	1.386	0.785	2.283
	(1.776)	(1.209)	(1.102)	(2.915)
ENTENTE	–0.861	–1.188*	–1.365*	–2.595
	(1.000)	(0.695)	(0.683)	(0.942)
NONAG	–1.499*	–1.839**	–1.835**	–2.709
	(1.041)	(0.575)	(0.573)	(0.839)
IMPT	66.110*	32.642	31.217	97.45
	(40.367)	(24.176)	(23.052)	(42.16)
BOTH		0.0595	0.065	0.734
		(0.283)	(0.281)	(0.395)
DEMO		–1.328		0.0357
		(0.404)		(0.778)
IMMED	0.265	–0.700		–1.447
	(0.472)	(0.606)		(0.677)
EXIST	0.993*	–0.520*	–0.310	–0.651
	(0.472)	(0.315)	(0.308)	(0.503)
Cut1	–5.368	–4.970	–4.270	–3.918
	(0.981)	(0.601)	(0.518)	(0.743)
Cut2	1.435	0.717	1.186	0.322
	(0.515)	(0.407)	(0.348)	(0.563)
n	366	366	366	156
χ^2	40.19	34.38	21.48	33.73

NOTE: Standard errors are in parentheses.
*$p < .05$. **$p < .01$.

TABLE 7

Mean Predicted $X_c\beta_c$ Values for the Ordered Probit Analyses across Various Portions of the Sample

Predicted Alliance Reliability	*Mean (Xβ) Model 5*	*Mean (Xβ) Model 6*	*Mean (Xβ) Model 7*	*Mean (Xβ) Model 8*
h(BC|Bigwar)	–0.0273	–0.682	–0.235	–0.189
h(BC|War)	–0.389	–0.737	–0.214	0.0869
h(BC)	–0.520	–0.914	–0.209	0.1478
h(BC|SQ)	–0.458	–0.882	–0.143	0.3181
h(BC|ACQ)	–0.549	–1.258	–0.389	–0.240

TABLE 8

t Test That the Predicted Xβ Values Are the Same in All Portions of the Sample

	h(BC|War)	*h(BC)*	*h(BC|SQ)*	*h(BC|ACQ)*
h(BC|Bigwar)				
Model 5	1.03	1.99*	2.58*	2.34*
Model 6	0.65	3.01**	2.44*	3.41**
Model 7	0.33	0.43	1.43	2.14*
Model 8	2.62**	0.0025	4.25**	0.690
h(BC|War)				
Model 5		0.99	1.98*	1.77*
Model 6		3.41**	2.59**	8.09**
Model 7		0.13	1.60	3.33**
Model 8		0.81	2.81**	3.48**
h(BC)				
Model 5			1.34	1.29
Model 6			0.85	6.44**
Model 7			2.24*	4.22**
Model 8			3.10**	4.89**
h(BC|SQ)				
Model 5				0.44
Model 6				6.46**
Model 7				5.25**
Model 8				6.35**

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

two variables have the same mean.[13] The test compares the distribution of two variables—for example, h(BC|Bigwar) and h(BC|ACQ)—and calculates

13. The *t* test is performed assuming that the variables have the same variance. This is the relevant null because the test is to determine whether the variables have the same distribution. The results are similar if the test is performed assuming different variances. It should be noted that several pairs of categories have nonempty intersections. In these cases, the *t* test is strictly appropriate. However, I include all comparisons for completeness.

how likely it is that the expected value of each is the same. If the expected values differ, this suggests that the expected reliability of an alliance affects the likelihood of conflict. The *t* test provides a statistical test of whether the effects of sampling are important. As Table 5 shows, the null hypothesis that sampling effects do not matter is rejected.

The true difference in alliance reliability between events that end in war and events that end in acquiescence may be much larger than 7%. Given that the null hypothesis is rejected, sampling effects bias parameter estimates. Specifically, the selection effect reduces the magnitude of the parameter estimates from their true value. The test of mean reliability underestimates the differences between different portions of the sample.

The analysis is repeated using ordered probit on the trichotomous dependent variable Hon3 (see Table 6).

Ordered probit analyses predict the probability that different events occur. Rather than compare the predicted probability of each event, Table 7 contains comparisons of the predicted $X_c\beta_c$^ values across different portions of the sample.

Again, *t* tests can be used to decide whether the differences in the mean values across the various portions of the sample are statistically significant. The null hypothesis that sampling is unimportant is again rejected. Alliance reliability affects A's and B's decisions concerning the initiation of conflict (see Table 8).

CONCLUSIONS

Alliances increase the probability of third-party intervention in wars. A nation that expects to receive allied support is likely to resist if attacked. The threat of allied intervention can also deter a nation from attacking in the first place. Whether a nation will intervene or not affects the behavior of other nations. The greater a nation's expectation that its allies will support it, the more likely it is to undertake actions that can lead to war. As the reliability of their enemies' alliances increase, nations behave in ways to avoid wars. Alliances are related to the occurrence of war because they affect third-party intervention.

The prospect of intervention affects the behavior of nations prior to a war. This has serious implications for studying alliance reliability. The intervention decision can be observed only when a war occurs. However, the likelihood that a nation will intervene affects whether a war occurs in the first place. The value of the dependent variable, whether a nation intervenes, affects whether the event is included in the sample. The empirical test developed in this article rejects the null hypothesis that sampling effects are unimportant. The estimates of alliance reliability obtained through a Heckman two-step procedure also support the theory's predictions. These tests show that alliance reliability affects the decisions that other nations make. Thus alliance reliability affects whether nations decide to attack and whether nations decide to resist. In addition, the direction of the bias is consistent with the theory: a nation with a defensive alliance is more likely to retaliate when attacked if the alliance is reliable. Comparing events that ended in war with those that ended in acquiescence reveals that alliances are more reliable in the former than in the latter cases. This is a result of a biased sample. It does not mean that alliances are more reliable when a nation retaliates; instead, it means that a nation is more likely to retaliate when it expects the support of its allies.

Unfortunately, sample bias results in inconsistent estimators. Because the decision to retaliate is made contingent on the decision to intervene, the error terms in B's decision to retaliate and C's decision to intervene are correlated. The parameter estimates obtained by probit analysis are not the true parameter values. Even with an infinite sample, the estimators would not collapse to the true parameter values. Generally, sample bias means that the magnitude of the estimated parameter values is less than that of the true parameter.

This article has considered how alliance reliability affects the occurrence of war. By developing a simple test, I have shown that nations consider alliance reliability when contemplating violent acts. The results show that nations with reliable allies are more likely to behave in a manner that leads to war, whereas nations with unreliable allies tend to behave more passively. Unfortunately, the interdependence between alliance reliability and the occurrence of war creates sampling problems for estimating alliance reliability. Whether the reliability of an alliance is observed depends on whether an event ends in war. However, alliance reliability affects the occurrence of war. The value of the dependent variable, alliance reliability, affects whether one can observe the dependent variable. The results show that this sample bias cannot be ignored in estimating alliance reliability. These results should be seen as preliminary because they highlight problems rather than solve them. However, they demonstrate that sampling effects are real impediments to empirical research and not just a nicety of econometric theory. To overcome selection effects, it is necessary to understand the processes by which an event is incorporated into the sample. Consistent estimates are produced only if the equation of interest and the selection of an event into the sample are simultaneously estimated.

APPENDIX

This appendix contains two sections. The first section estimates alliance reliability via a Heckman two-step procedure. The second section compares analyses using different coding decisions.

HECKMAN TWO-STEP ESTIMATION PROCEDURE

As discussed in the main text, sample selection produces biased estimates because the expected value of the stochastic error term is nonzero. For simplicity, I start by considering only B's and C's decisions: those events in which an attack has occurred. Using the notation developed in the main text, if B retaliates, then $Y_b^* \geq 0$. The expected value of e_c is nonzero if e_c and e_b are correlated: $E[e_c | Y_b^* \geq 0] = \rho\lambda(Z_b)$, where $\lambda(Z_b) = \phi(Z_b)/\Phi(Z_b)$. Heckman (1976, 1979) used this fact to control for sample bias. The procedure is as follows:

1. Estimate β_b using a probit analysis of B's decision to retaliate. This parameter estimate is used to estimate $\lambda(Z_b) = \phi(X_b\beta_b\hat{})/\Phi(X_b\beta_b\hat{})$, where $\phi(\ )$ is the standard normal density and $\Phi(\ )$ is the standard normal cumulative density function.
2. Add $\lambda(Z_b)$ as an additional independent variable in C's decision and analyze C's intervention decision using probit.

The Heckman approach provides consistent estimates if the second equation has a continuous dependent variable. Unfortunately, because I analyze the second equation using probit, the estimates of C's decision to intervene are inconsistent. Table 1A compares the estimates of a two-step Heckman procedure with a conventional probit analysis. The additional independent variables are defined as follows: AB relation is Bueno de Mesquita's (1981) utility measure for nations A and B; AB arms ratio is A's military capabilities divided by the sum of A's and B's capabilities (AB arms ratio = $cap_a/(cap_a + cap_b)$). The conventional probit analysis can be thought of as the Heckman procedure with the restriction that the parameter on the $\lambda(Z_b)$ term is zero. A likelihood ratio test determines whether this linear restriction significantly affects the analysis. The likelihood ratio, twice the difference between the log likelihoods of the restricted and unrestricted models, is asymptotically distributed χ^2 with 1 degree of freedom. The analysis in Table 1A rejects the null hypothesis of no selection effect at the 5% level of significance.

I extend the Heckman procedure to the three-equation model in the following manner:

(continued)

APPENDIX Continued

TABLE 1A
Comparison of a Heckman Two-Step Estimation with a Single-Equation Probit Model

	Heckman Two-Step Procedure		*Single-Equation Model*
Independent Variable	*B's Decision to Retaliate:* Y_b	*Hon:* Y_c	*Hon:* Y_c
AB relations	0.471**		
	(0.0944)		
AB arms ratio	0.677**		
	(0.156)		
Constant	–0.312	–0.181	–0.720
	(0.159)	(0.280)	(0.166)
TIME	–0.036	–0.013	–0.016
	(0.110)	(0.144)	(0.143)
DELTA	0.383**	0.337	0.463*
	(0.140)	(0.211)	(0.200)
EU	1.988**	–1.768	–0.885
	(0.766)	(1.058)	(0.944)
ENTENTE	–0.538**	–0.834	–1.176*
	(0.179)	(0.564)	(0.534)
NONAG	–0.210	–0.730*	–0.886*
	(0.142)	(0.365)	(0.350)
IMPT	–38.797**	72.630**	45.795*
	(14.122)	(24.168)	(20.636)
$\lambda(Z_b)$		–2.111*	
		(0.888)	
n	719	364	364
χ^2	80	34	28.31
LogLikelihood	–458	–172	–175
Likelihood ratio test = 5.84*			

NOTE: Standard errors are in parentheses.
$*p < .05$. $**p < .01$.

1. Estimate A's decision to attack using probit.
2. Use these estimates to calculate $\lambda(Z_a) = \phi(X_a\beta_a\hat{}\,)/\Phi(X_a\beta_a\hat{}\,)$.
3. Use probit to estimate B's decision to retaliate; include $\lambda(Z_a)$ as an additional independent variable.
4. Use the estimates of B's decision to calculate $\lambda(Z_b) = \phi(X_b\beta_b\hat{}\,)/\Phi(X_b\beta_b\hat{}\,)$.
5. Add $\lambda(Z_a)$ and $\lambda(Z_b)$ as additional independent variables in C's decision and analyze C's intervention decision using probit.

The results of this iterative application of Heckman's procedure are shown in Table 2A. The conventional probit analysis provides comparison. The

TABLE 2A

Comparison of a Heckman Two-Step Estimation Iteratively Applied to a Three-Equation Model and a Single-Equation Probit Analysis

	Heckman Two-Step Procedure Iteratively Applied to a Three-Equation Model			*Single-Equation Model*
Independent Variable	*A's Decision to Attack: Y_a*	*B's Decision to Retaliate: Y_b*	*Hon: Y_c*	*Hon Restricted: Y_c*
AB relation	–0.519**	5.687**		
	(0.063)	(0.891)		
AB arms ratio	0.913**	–8.497**		
	(0.102)	(1.563)		
Constant	–0.487	–0.342	–1.965	–0.720
	(0.100)	(0.160)	(0.469)	(0.166)
TIME	–0.203	0.124	–0.163	–0.016
	(0.069)	(0.115)	(0.154)	(0.143)
DELTA	–0.203*	2.310**	0.304	0.463*
	(0.088)	(0.354)	(0.213)	(0.200)
EU	–2.680**	30.140**	–3.352**	–0.885
	(0.345)	(4.858)	(1.091)	(0.944)
ENTENTE	0.029	–0.932**	–0.763	–1.176*
	(0.122)	(0.193)	(0.569)	(0.534)
NONAG	–0.067	0.310	–0.742*	–0.886*
	(0.095)	(0.168)	(0.373)	(0.350)
IMPT	20.399**	–260.575**	78.727**	45.795*
	(6.422)	(40.456)	(22.858)	(20.636)
$\lambda(Z_a)$		–38.155	4.706**	
		(6.486)	(1.181)	
$\lambda(Z_b)$			–1.206	
			(0.783)	
n	1,763	719	364	364
χ^2	155.77	115.94	49.68	28.31
LogLikelihood	–1,114	–440	–164	–175
Likelihood ratio test = 21.36**				

NOTE: Standard errors are in parentheses.
$*p < .05$. $**p < .01$.

likelihood ratio test rejects the null hypothesis of no selection effects at the 1% level.

COMPARISON OF ANALYSES USING DIFFERENT CODING DECISIONS

The data used in the first analysis in Table 3A are coded using every possible intervention that could occur. The second analysis uses the more

(continued)

APPENDIX Continued

TABLE 3A
Comparison of Model across Two Differently Coded Data Sets

Hon3	*Hon3* (*All Possible Interventions*)	*Hon3* (*Coding as in Main Text*)
TIME	–0.209	–0.260*
	(0.230)	(0.203)
DELTA	1.697*	1.702**
	(0.474)	(0.476)
ENTENTE	–0.896	–0.861
	(0.986)	(1.000)
NONAG	–1.456*	–1.499*
	(1.037)	(1.041)
DEMO	–0.609	–0.678
	(0.617)	(0.596)
EU	–0.469	–0.114
	(2.795)	(1.776)
IMMED	0.376	0.265
	(0.797)	(0.565)
EXIST	0.997**	0.993*
	(0.480)	(0.472)
IMPT	70.713**	66.110*
	(30.895)	(40.367)
Cut1	–5.227	–5.368
	(1.022)	(0.981)
Cut2	1.567	1.435
	(0.592)	(0.515)

NOTE: Standard errors are in parentheses.
$*p < .05$. $**p < .01$.

selective decision of intervention used in the main text. The similarity of the analyses demonstrates that the results are not simply a function of coding decisions.

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