UNCERTAINTY OF THE LIBERAL PEACE[*]

CULLEN F GOENNER
Department of Economics, University of North Dakota

Abstract

Variable selection is a crucial aspect of formulating a model to empirically examine data as omitted variables can create spurious association, while inclusion of irrelevant variables can bias the results of one's estimates. To mitigate such problems researchers rely on theory to guide their selection of variables to include in their models. Unfortunately it is often the case in social science that there exist several plausible theories to explain actions, and hence several models which researchers can use in their empirical work. This lack of unique theory is evident in examining trade's effect on conflict, as there are three main theories that each suggests a different effect for trade interdependence on conflict. Empirically the effect of trade on conflict remains uncertain, as researchers Barbieri and Oneal & Russett using different measures of trade interdependence (models) have come to disparate conclusions. Each of their inferences is based on the belief that the variables they select form the "true" model that generates the data. The problem is that theory is unable to indicate whether one model is more appropriate than another, which creates uncertainty over the empirical effects of trade on conflict. To account for uncertainty in model selection I allow for several models by applying Bayesian model averaging (BMA) to the study of conflict. Accounting for this uncertainty, I find that trade interdependence does not have a significant effect on the prediction of militarized conflict, whereas joint democracy continues to reduce conflict.

Introduction

In the past several years researchers have been increasingly interested in whether the empirical existence of the democratic peace extends to that of a liberal peace in which trade interdependence in addition to democracy inhibits conflict. The reason for such interest is due to policymaker's desire to know whether engaging in trade with foreign nations is constructive in the sense that it reduces conflict. Theoretically the effects of trade on conflict are uncertain. Liberals theorize a negative relationship between trade and conflict, Marxists theorize a positive relationship, and realists theorize that there is no relationship.

Empirical researchers have been unable to settle this debate. While most researchers (Oneal & Ray, 1997; Oneal & Russett, 1997, 1999; Russett, Oneal, & Davis, 1998; Russett & Oneal, 2001) have found that trade reduces conflict there exists sufficient evidence to the contrary (Barbieri, 1996, 1998, 2002; Beck, Katz, & Tucker, 1998) to question the empirical effects of trade.[1]

Representing the two sides of this empirical debate is the work of Barbieri (1996, 1998, 2002) and Oneal & Russett (1999). Barbieri (1996, 1998, 2002) using controls similar to those of others and three measures of trade interdependence finds that trade interdependence increases the probability that states engage in militarized conflict. Barbieri's findings though are largely contradicted by the work of Oneal & Russett (1999). Using an alternative measure of trade interdependence and replicating the methods used by Barbieri, Oneal & Russett (1999) find that the sign and significance for trade's effect changes. In drawing their conclusions each of these authors assumes, as is standard in the literature, that the variables they have selected form the 'true' model that explains the data. The difficulty in this is that there are several theories that explain conflict and hence several candidate variables researchers may choose from in forming a model. As Beck, King, & Zeng (2000) note the sensitivity of Barbieri (1996) and Oneal & Russett's (1999) findings to their model specification creates uncertainty over the effects of trade on conflict.

In the following analysis of interstate conflict I allow for uncertainty in model selection by assuming that the researcher knows the list of candidate variables that form the true model, but does not know which combination of these variables form the true model. This weakens the assumption that the researcher has strong prior information on which model generates the data. The candidate variables that I consider are those used by Barbieri (2002) and Oneal & Russett (1999). The different linear combinations of these variables form a set of models, of which, one is the model that generates our data. By using Bayesian methods to average over the models supported by the data, I find that trade interdependence as measured by Barbieri (2002) and Oneal & Russett (1999) has no role in predicting conflict, while joint democracy continues to reduce conflict.

Trade and Conflict

The liberal theory of international relations (Doyle, 1997; Rosecrance, 1986) is that trade between nations creates dependence between nations that foster peace. With trade, nations are able to specialize in the production of goods in which they have a comparative advantage, and by trading each is able to lower their opportunity cost of production and increase their output above that possible without trade. Trade thus provides economic benefits and dependence among trading partners, which create costs that inhibit these pairs of states from engaging in conflict. Polachek (1980) was the first to formally incorporate these ideas into a model relating trade to conflict. His empirical testing of this model indicated that trade increased cooperative events and decreased conflict between countries.

Trade not only has an economic effect on individuals, but also a sociological effect in that there are multiple channels which connect societies (Keohane & Nye, 1989). For instance the interaction of nongovernmental elites of dissimilar backgrounds allows for the creation of ties that form norms that inhibit conflict (Russett, 1967). This relation between trade and international relations has been referred to by Montesquieu as the spirit of commerce. As Montesquieu states "the spirit of commerce brings with it the spirit of frugality, of economy, of moderation, of work, of wisdom, of tranquility, of order, and of regularity." (quoted in Hirschman 1977: 71). Such ideas are also expressed by Kant's cosmopolitan law in which access to trade and exchange by individuals is one of the keys to achieving peace between nations.

Marxists and neo-mercantilists though theorize that trade can lead to conflict between states. Hirschman (1945) recognized that, while two countries gain from trade, the benefits are rarely equal. Thus the distribution of gains is important to international relations, as asymmetric interdependence may be a source of power. It is this asymmetric dependence that Keohane & Nye (1989: 10-11) believe are "most likely to provide sources of influence for actors in their dealings with one another." Nations not dependent on a particular trading partner may use other's dependence on them to their advantage by using trade to manipulate their partner's actions. Hirschman (1945) describes that Nazi Germany pursued trade policies with Eastern Europe to such ends. In response states that are economically dependent on others may use militarized means to end this outside influence and obtain more favorable trading terms.

Whereas liberals and Marxists both hold that trade influences conflict, the realist theory of international relations suggests that trade is irrelevant to relations between states (Buzan, 1984; Gilpin, 1987). Realism asserts that states struggle to exist within an anarchic system, and thus their primary concern is with survival. Survival, realists argue, necessitates that states must often subsume economic interests in order to balance military power. Eckes (1992) notes several instances in which US Presidents since Truman have placed foreign policy objectives ahead of economic objectives. In rebuilding Japan and Europe, the United States opened their markets and lowered their tariffs on imports from Japan and Europe without concessions from these countries and strong opposition from the Commerce Department. Economic interdependence was a result of the strategic nature of the bipolar system that existed after 1945 and not a significant cause of peace. Observed relations between trade and conflict Gowa & Mansfield (1993) explain do not imply a causal relationship but are the result of common interests. Trade between allies creates positive externalities with regards to security. Thus common interests, which are important in a bipolar system, lead to increased trade and reduced levels of conflict.

The liberal argument that trade reduces conflict relies on the notion that trade creates economic and sociological ties between individuals of different countries that are difficult to be broken. This though fails to recognize the political economy of trade in that while a society as a whole gains from trade, industries that compete with imported goods will be adversely affected. This results in worker displacement and economic despair in communities where these industries are located. Such negative effects can generate resentment for foreign countries. For instance, consideration is currently being given to reducing the over 200% tariff on sugar imports. Increasing the trade of sugar will lower its price in the US, which is three times higher than the world price. This will benefit consumers by lowering the prices of goods using sugar, as well as industries that rely on sugar as a key input of production. Increasing interdependence though will have a sharply adverse effect on domestic production of sugar cane and sugar beets as well as in the refining of sugar. In cases such as this in which the majority of people gain a little, but a minority loses a lot, the latter are often more effective in organizing to convince the majority and decision makers for protection. Increased trade of strategic or protected goods is unlikely to result in ties between countries. For most goods it may be that the positive ties formed by the majority are offset by those of the minority, in which case trade would not offer clear ties between countries. Evidence of which can be seen in the current political debate over NAFTA and other trade agreements.

Model Uncertainty

Multivariate regression analysis requires researchers to choose the relevant set of variables to include in the model specification. While theory may support the choice of some variables, often the choice of what to include or exclude will be arbitrary. In this case several model specifications are theoretically supported. When the effects of the variables of interest are sensitive to model specification it creates uncertainty in the interpretation of the results. For instance suppose one researcher selects covariates M* to estimate the probability of conflict, and finds that M* fits the data and makes sensible predictions according to their prior beliefs. Another researcher selects an alternative set of covariates M** that provides as good of fit but leads to substantially different estimated effect sizes, different standard errors, or different predictions. Which model is correct? Hoeting et al. (1999: 383) state that 'basing inferences on M* alone is risky; presumably ambiguity about model selection should dilute information about effect sizes and predictions . . .' The effects of model uncertainty are evident in the sensitivity of Barbieri (1996, 1998, 2002) and Oneal & Russett's (1999) results to model specification.

Barbieri (1996) represents an attempt to empirically assess the effect of economic interdependence on interstate conflict. To test the effects of interdependence one must be able to construct a measure of interdependence between nations. Measuring interdependence, Barbieri (1996: 36) notes, is difficult because there is an 'absence of a clear consensus about what the phenomenon entails and how it should be measured.' The problem Barbieri finds is that while theorists provide clues to the relevant conditions that breed conflict, they rarely speak as to how to measure them. Barbieri (1996) uses state A's trade with state B divided by state A's total trade as a measure of state A's dependence on state B. The measure reflects a state's dependence on a particular partner for their trade, rather than dependence on trade in general as suggested by Oneal et al. (1996). Guiding her choice of dyadic trade/total trade as a measure of dependence were data limitations to the 1870-1938 period analyzed.[2]

Recognizing that several theories explain trade's effect on conflict, Barbieri includes three transformations (salience, symmetry, and interdependence) of the dependence measure. Salience is included to measure whether a trading relation is important to both nations, the more salient trade is the less likely one would experience conflict under the liberal hypothesis that trade reduces conflict. Asymmetric relations were said to potentially create conflict, thus symmetry measures whether states are equally dependent on each other for trade. The variable interdependence is designed as an interaction term between salience and symmetry. Barbieri (1996) uses these variables along with others common to the literature as controls in her regression analysis of the probability of conflict.[3] The results from the regression analysis of 1870-1938 suggest that trade interdependence increases the probability that states engage in militarized disputes. Barbieri (1998, 2002) using similar variables, but controlling for duration dependence as suggested by Beck, Katz, & Tucker (1998), also finds that her results are robust over the 1870-1992 period. The effects of model specification though can be seen in Barbieri's (1996) Table I, which shows that the sign of the coefficients for the trade variables differ across four models. Uncertainty about variable and model selection creates uncertainty about inference that is based on a single model. Barbieri's (1996, 1998, 2002) conclusions, which are based on the 'full model,' are thus subject to question.

While uncertainty is created by variable selection it is also created by variable measurement. Oneal & Russett (1999) offer an alternative measure of dependence that is equal to a state's dyadic trade divided by GDP. This measure Oneal & Russett (1999: 425) view as superior to that based on total trade 'because states differ markedly in the degree to which they are autarkic.' Further adding that a 'state's trade may be concentrated, but this is unlikely to restrain it from using force against its commercial partner if its dependence on trade is limited.' While this statement is reasonable, it is equally likely that states that have many important trading partners will not be concerned with the threat of lost trade from a minor trading partner (See Gasiorowski, 1986). Furthermore Mansfield & Pollins (2001) question whether bilateral trade as a fraction of GDP is an adequate measure of the vulnerability that interdependence is said to create. Barbieri's measure of trade salience they add might be able to reflect the ability of countries to substitute trading partners. From this both measures seem theoretically valid in that the concentration and relative importance of trade influence whether states are interdependent. Oneal & Russett (1999) using their measure of dependence to construct salience, symmetry, and interdependence replicate the methods and other controls used by Barbieri (1998) to test the effects of their measure of dependence on conflict. They show that using their measure of dependence results in changes of sign and significance in the coefficients of the trade variables.

Oneal & Russett (1999) in their analysis also consider an alternative model specification, which they prefer to that used by Barbieri (1998). To control for trade interdependence they favor using the lower and higher trade to GDP ratios of each pair of states instead of Barbieri's (1998) more complicated combinations of these variables. Further to better control for the effects of distance they also include the log distance between states' capitals in their model specification. The results of their preferred model specification indicate that increasing the dependence of the least dependent state, weakest link, reduces conflict.

Bayesian Model Averaging

From Barbieri (2002) and Oneal & Russett's (1999) analyses one can see that standard regression techniques, while capable of estimating the coefficient for interdependence, are unable to determine whether either model generated the data they examine. Classical hypothesis tests allow us to compare competing model specifications, though they often offer little insight. For instance, Davidson & MacKinnon's (1981) J-Test uses the encompassing principal (Greene 1997: 365) to determine whether a model can explain the features of its competitors. Consider the following two model specifications, where the explanatory variables in *x* are not a subset of *z* and those in *z* are not a subset of *x*:

$$H_0: \; y = \beta x + u_0$$
$$H_1: \; y = \gamma z + u_1$$

To apply the J-Test (Maddala, 1992) to test H_0 against H_1, first, estimate the second equation and obtain the fitted values $\hat{y}_1 = \hat{\gamma} z$. Next estimate the regression equation $y = \beta x + \alpha \hat{y}_1 + u$ to test the hypothesis that $\alpha = 0$. If the hypothesis is rejected, then H_0 is rejected in favor of H_1. Otherwise H_0 is not rejected by H_1. A test of H_1 against H_0 is similar. Estimate the first equation and use the fitted values to estimate the regression equation $y = \gamma z + \delta \hat{y}_0 + v$. Conduct a similar hypothesis test of $\delta=0$.

Testing the null hypothesis of Barbieri's (2002) model specification versus the alternative of Oneal & Russett (1999), the J-Test reveals that Barbieri's model is rejected in favor of Oneal & Russett's model ($\hat{\alpha} = .953, t = 11.15$). Unfortunately when the hypotheses are reversed, Oneal & Russett's model is rejected in favor of Barbieri's model specification ($\hat{\delta} = .678, t = 3.26$). In this case one is uncertain to which model is preferred. Even in cases in which the results are conclusive, this type of test can only tell us the true model if we assume that one of the models being tested is the true model.

In the analysis of conflict below it is assumed that there are several possible regressors that causally explain the dependent variable and thus several combinations of these variables (models $M_1 \ldots M_K$) that researchers may select, of which one is the 'true' model that generates the data. To account for uncertainty in model specification, Bayesian model averaging is used.[4] As Bartels (1997) has shown a Bayesian perspective provides a natural way to approach competing model specifications. Rather than simply rejecting one model in favor of another, the Bayesian approach compares models to determine which has the higher probability of being the true model. Averaging over the results of the most likely models allows us to account for model uncertainty in the analysis of conflict.

To estimate the effect of a parameter in the presence of model uncertainty one calculates the posterior distribution of the parameter given the data D as:

$$P(\beta / D) = \sum_{k=1}^{K} P(\beta / M_k, D) P(M_k / D) \tag{1}$$

The posterior distribution $P(\beta/D)$ is a weighted average of the posterior distribution under each of the K models, with weight equal to the posterior model probabilities $P(M_k/D)$. By Bayes' rule and the law of total probability the posterior model probability is

$$P(M_k / D) = \frac{P(D / M_k) P(M_k)}{\sum_{l=1}^{K} P(D / M_l) P(M_l)} \tag{2}$$

where $P(D/M_k)$ is the likelihood and $P(M_k)$ is the prior probability that model M_k is the true model, given one of the K models is the true model. If a non-informative prior is assumed in which each of the K models are equally likely to be the true model ($P(M_1) = \ldots P(M_k) = 1/K$) then the posterior model probability becomes:

$$P(M_k / D) = \frac{P(D / M_k)}{\sum_{l=1}^{K} P(D / M_l)} \tag{3}$$

The integrated likelihood is given by

$$P(D/M_k) = \int P(D/\beta_k, M_k) P(\beta_k/M_k) d\beta_k \tag{4}$$

where β_k is a vector of parameters (coefficients and variance), $P(D/\beta_k, M_k)$ is the likelihood and $P(\beta_k/M_k)$ is the prior density of the parameters under model M_k. Using the Laplace method for integrals Raftery (1995) shows that the integrated likelihood of model k is approximately equal to exp(-½ BIC_k) where BIC_k is the Bayesian information criterion of model k. Schwarz (1978) shows that the BIC is

$$BIC_k = -2\log(\hat{L}) + d_k \log(N) \tag{5}$$

with $\hat{L}$ equal to the maximized likelihood under model k, d_k is the number of parameters in model k, and N is the sample size. The second term penalizes more complex models. Using the approximation of $P(D/M_k)$ = exp(-½ BIC_k) and the prior assumption that models are equally likely the posterior model probability becomes:

$$P(M_k/D) \approx \frac{\exp(-\frac{1}{2}BIC_k)}{\sum_{l=1}^{K}\exp(-\frac{1}{2}BIC_l)} \tag{6}$$

Once the posterior distribution has been determined one can summarize the effects of the parameters on the dependent variable by calculating the posterior mean, posterior variance, and posterior effect probabilities. Raftery (1995) reports the posterior mean and variance can be approximated by

$$\begin{aligned} E(\beta_1/D, \beta_1 \neq 0) &\approx \sum_{A1} \hat{\beta}_1(k) P(M_k/D) \\ Var(\beta_1/D, \beta_1 \neq 0) &\approx \sum_{A1} [Var(k) + \beta_1(k)^2] P(M_k/D) - E(\beta_1/D, \beta_1 \neq 0)^2 \end{aligned} \tag{7}$$

where $\hat{\beta}_1$(k) and Var(k) are the maximum likelihood estimates and variance of β_1 under model k, and the summation is over models that include β_1 (set A_1).

To implement Bayesian model averaging one must specify the universe of models to average over, where a model refers to a particular set of regressors. Here it is assumed that we have *n* candidate variables to include in our regression, of which we are unsure of the combination that forms the 'true' model. Thus there are 2^n different models that are possible and make up the set of models to consider. With sixteen regressors the summation in equation 1 would be over 65,536 models and involve calculating the integrals implicit to the equation. Hoeting et al. (1999) outline two ways in which to manage the summation. The first, which is used in the analysis below, discards models that are not supported by the data. The second method uses Markov chain Monte Carlo model composition to approximate equation 1.[5]

Madigan & Raftery (1994) argue that models not supported by the data should not be included in equation 1 and appeal to what they refer to as Occam's Window to discard models. The first restriction of Occam's Window is to exclude models that predict the data sufficiently less than predictions of the best model, where predictions are based on the posterior model probability of each model $P(M_k/D)$. Models in set A' are included

$$A' = \{M_k : \frac{\max PMP_l}{PMP_k} \leq C\} \tag{8}$$

where C is a cutoff chosen by the researcher. The cutoff used in the analysis below is 20, which is the default of the program. Doubling the cutoff to 40 did not effect the results reported below. Determining set A' requires comparing each model's posterior model probability with that which is highest.

A second, optional, restriction removes complex models that receive less support than simpler models that are subsets. If a model within set A' is contained in another model and the simpler model has higher posterior model probability, then the more complex model is excluded. In the analysis below only the first restriction is used. This allows more models, with high posterior model probability, to be averaged over and provides as Raftery (1995) discusses better out of sample prediction than using both restrictions. This method of excluding models Hoeting et al. (1999) report often reduces the number of models to average over to fewer than ten.

Analysis

The purpose of this analysis is to account for uncertainty in variable selection when modeling the probability of militarized conflict. Uncertainty in variable choice creates uncertainty in the empirical effects of variables as is evident in the findings of Barbieri (2002) and Oneal & Russett (1999). To account for uncertainty in variable selection, I apply techniques of Bayesian model averaging to allow for the possibility that either of their models among others is the true model that generates the data. The regressors that I selected as candidate variables for the true model are from Barbieri's (2002) Table II and Oneal & Russett's (1999) Table II. Each uses the same measures of joint democracy, alliance membership, contiguity, and capability ratio as controls, yet differ in their choice of interdependence on trade measures and that Oneal & Russett (1999) include the distance between states and major power status.

A limitation of Bayesian Model Averaging (BMA) is that the researcher must make an assumption about the set of variables to be considered. It is important to remember that BMA makes weaker assumptions than previous empirical studies by accounting for uncertainty in model specification. Selection of the variables included in the universe of models was guided by the fact that their use by researchers has led to empirical results at odds with respect to the effect of trade on conflict. Barbieri's (1996) results indicated that model specification influenced her own results, as does the ongoing debate between Barbieri (2002) and Oneal & Russett's (1999) findings. While these variables are typical to the study of interstate conflict, they do not represent every variable used to study conflict. For instance researchers examine the effect of institutions (Mansfield & Pevehouse, 2003; Russett & Oneal, 2001; Russett, Oneal, & Davis, 1998) and preferences (Gartzke, 2000). A more comprehensive study of these alternatives and others is beyond the scope of this paper, but is of interest for further research.

The dependent variable examined below is the onset of militarized interstate disputes (MID), as defined by Gochman & Maoz (1984) and analyzed by Barbieri and Oneal & Russett. The variable is binary and takes the value of one for the first year a militarized dispute takes place between a pair of states. Subsequent years of the same dispute are discarded from the analysis. Variables to include as candidates for causing the onset of conflict are those that capture the willingness and ability of states to engage in conflict.[6]

Empirical research (Barbieri, 1996, 1998, 2002; Beck, Katz, & Tucker, 1998; Oneal & Russett, 1997, 1999) has shown consistently that democratic pairs of states are less likely to engage in conflict. Controlling for this influence is the variable *Joint Democracy*, which combines the political regime type of each state within a pair of states to form a measure of regime type for the pair. The measure of regime type comes from Jaggers & Gurr's Polity III (Jaggers & Gurr, 1995) data set, where states range from fully democratic (+10) to fully undemocratic (-10).[7] The measures of state and dyad regime type are ordinal in nature, which is to say that states that score 10 on Jaggers & Gurr's index are not 10 times more democratic then those that score 1. Joint democracy (JNTDEM) for a dyad, consisting of country A and country B equals:[8]

$$JNTDEM_{AB} = (DEMOC_A + 10) * (DEMOC_B + 10) \tag{9}$$

Allies are defined by the Correlates of War (COW) project as nations that have formally agreed to a defense pact, neutrality pact, or entente. The binary variable *Allies* takes the value 1 if regimes within the dyad are allied with each other. Formation of an alliance requires agreement on a common goal. Common interests increase the benefits of compromise, thereby promoting the peaceful settlement of disputes. Contiguity and distance capture the idea that conflicts of interest typically involve neighboring states. Most interactions between regimes are regional in nature due to the positive relation between distance and interaction cost, thus giving contiguous states the motive and opportunity for conflict. *Contiguity* is a binary variable that takes the value 1 if states share a border or are separated by less than 150 miles of water either directly or indirectly via dependencies. *Distance* measures the logarithm of the great circle distance between states' capital cities or in some cases major ports.

Capability ratio is used to measure a country's means to engage in military war. The ratio is derived from COW data comprised using each country's share of military personnel, military expenditures, iron and steel production, energy consumption, urban, and total population. The variable *Capability Ratio* is the logarithm of the ratio of the larger to lower state. *Major Dyad* is a binary variable that takes the value 1 if either state within the dyad is what Singer & Small (1994) define as a major power.[9] These are states which are assumed to be the most active in global affairs.

Barbieri (2002) and Oneal & Russett (1999) also include in their analyses four variables that are designed to control for the duration dependence of observations. The idea is that pairs of countries that have previously interacted peacefully are less likely to engage in conflict. Following the recommendation of Beck, Katz, & Tucker (1998) they form a natural cubic spline with three knots on the number of previous years of peace, which generates the four *Peace Year* variables.

Where Barbieri (2002) and Oneal & Russett's (1999) models primarily differ is in their measurement of trade dependence and interdependence. Barbieri prefers a measure of trade dependence based on the concentration of trade and Oneal & Russett prefer a measure based on the relative importance of trade. The result is that Barbieri's measure of country A's dependence on state B divides the sum of the dyad's exports and imports by state A's total trade, whereas Oneal & Russett divide by state A's GDP. One can construct similar ratios for state B. For further discussion of the relationship between these measures see Gartzke & Li (2003) and the responses to their work by Barbieri & Peters (2003) and Oneal (2003).

To measure the influence of interdependence Barbieri combines her measures of trade dependence for both states within each dyad to form dyadic measures of the salience, symmetry, and interdependence of trade using the transformations below.

$$\begin{aligned} SALIENCE_{AB} &= \sqrt{DEPEND_A * DEPEND_B} \\ SYMMETRY_{AB} &= 1 - \left| DEPEND_A - DEPEND_B \right| \\ INTERDEP_{AB} &= SALIENCE * SYMMETRY \end{aligned} \tag{10}$$

To calculate interdependence Barbieri (2002) standardizes *Salience* and *Symmetry* by subtracting the mean value of each variable from each observation and then dividing the calculated value by the standard deviation. As Barbieri (2002) notes this reduces collinearity between the trade measures and also assures that salience and symmetry contribute equally to the interaction term. Oneal & Russett's measures of trade interdependence are based on their assumption that the state that is less dependent on trade within each dyad has fewer economic constraints to initiate conflict. To control for this they include *Lower Dependence*, which is the lower dependency score within the dyad. *Higher Dependence*, the higher dependency score within the dyad, is included to capture the effects of the symmetry of trade.

To create the data set used here I merge Oneal & Russett's (1999) data with Barbieri's (2002) trade data.[10] The data covers the 1950-1992 period and consists of observations from 107,339 pairs of states. The independent variables have all been lagged one year to avoid problems associated with regressors, such as trade at time t, which are influenced by the dependent variable at time t. Given the binary nature of the dependent variable, logistic regression is used to model the probability of militarized dispute for a pair of states. Results from logistic regression analysis of these data using Barbieri's (2002) model specification appear in columns 1 and 2 of Table I and those of Oneal & Russett (1999) appear in columns 3 and 4. As we can see from these results the choice of dependence measure affects the sign and significance of the coefficient for trade interdependence, leaving researchers uncertain to the effect of trade on conflict.

[TABLE I about here]

To apply Bayesian model averaging to the above data I use the S-Plus function *biclogit* version 2.0 written by Raftery & Volinsky (1996). *Biclogit* calculates for logistic regression models the posterior mean, variance, and effect probabilities as well as reports the posterior model probabilities of the models averaged over. The program uses an algorithm adapted from Furnival & Wilson (1974) to eliminate large blocks of models without having to compare each of the 2^n models. The Bayesian Information Criterion is then determined for each of the remaining models and Occam's window is applied to determine the models to average over.

Researchers must also specify for each model a prior probability that the model considered is the 'true' model. The subjective determination of the prior distribution is often seen as a limitation of Bayesian statistics. Raftery (1995: 127) though notes that in large samples this choice has 'very little influence' on the posterior mean and variance. In the analysis that follows I assume the regressors and models have equal prior probabilities, given Hoeting et al. (1999) suggestion that this is a neutral choice when there is little information about the relative plausibility of models. In some cases theory may guide the choice of priors. For instance Bartels (1997) in his analysis considers two alternative sets of priors in addition to uniform priors. Dummy resistant priors discount models that include dummy variables with no *a priori* theoretical foundation, while search resistant priors discount models selected through search methods that are perceived to be theoretically less likely *a priori*. In the study of trade's influence on conflict one might presume that the effect of the concentration of trade will not be independent of that for the relative importance of trade. Further the relevance of one 'realist' or 'liberal' variable may indicate the importance of others. Additional research needs to consider the interconnection between and within the ‘realist’ and ‘liberal’ theories in order to improve on the uniform priors used below.

Results

Model uncertainty is evident in the prediction of interstate conflict as eight models are selected within Occam’s window. The specification of these models appears in Table II. The model with the highest posterior model probability accounts for 41% of the total posterior model probability, which is to say that the data support several models as being the true model. From these results one can see that neither Barbieri (2002) or Oneal & Russett’s (1999) model specifications are selected, which means that the PMP of these models are at least 20 times less than that of the best model. In addition, none of the models selected include any of the measures of trade interdependence in their specification.

[TABLE II about here]

The estimates reported in Table III, generated by BMA, account for uncertainty in model specification by averaging over the estimates of each of the eight models, with the weight of each estimate given by its posterior model probability. Table III provides the posterior mean, standard deviation, and effect probabilities for each of the variables. The first two values are similar in interpretation to the coefficient and standard error in standard analyses. The latter value, the posterior effect probability, represents the posterior probability that the coefficient is not equal to zero. Raftery (1995) provides a rough guide to interpreting the posterior effect probabilities in citing 50-75%, 75-95%, 95-99%, and 100 % as weak, positive, strong, and very strong evidence of a variable having an effect.

[TABLE III about here]

The uncertainty over trade's effect on conflict is to whether or not trade has an effect and if so whether it reduces or increases interstate conflict. The results here suggest that trade does not have an effect on conflict as the data do not support trade variables being included in the model specification. As a result the posterior effect probabilities of the trade variables are zero and no estimates of these variables are generated. While the results do not support that trade interdependence reduces conflict, they do provide strong evidence for the proposition that joint democracy reduces conflict. The posterior mean of joint democracy is -.0034 and significant with $\Pr(\beta \neq 0/D) = 100\%$.

With respect to the other controls, *Distance*, *Contiguity*, and *Major Power* receive very strong support for having an effect on conflict as each appears in the eight models selected to be averaged over, which corresponds to a posterior effect probability of 100%. *Allies* appears in six of the eight models and receives strong support with a posterior model probability of 95.6%. *Capability ratio* though receives little support with a posterior model probability of 44.6%. The estimated coefficients of these variables are consistent with what theory predicts. Contiguous states are more prone to conflict as are states that are less separated by distance. Pairs of states consisting of at least one major power are also more likely to engage in conflict, while those allied are less likely. Increasing the capability ratio is found to reduce the incidence of conflict.

Oneal & Russett (1999) argue that their analysis of all pairs of states masks the effects of trade because of the large number of states that have no interaction with each other. Limiting analysis to 'politically relevant' (See Maoz & Russett, 1992) pairs of states, which are either contiguous or consist of at least one major power, they show that trade interdependence has a more significant effect on reducing conflict. Bayesian model averaging applied to the subset of 'politically relevant' dyads did not uncover any effect of trade on conflict. Three model specifications were selected (Table IV), none of which included any of the trade measures. Among this subset of dyads, the capability ratio has a stronger effect on conflict whereas the effect of distance is weakened. The other effects of the variables remain largely the same and are reported in Table V.

[Tables IV and V about here]

A final BMA analysis was conducted using Gleditsch's (2002) version 2.1 trade data. The purpose of this analysis is to verify that the results reported above are not driven by the treatment of missing data by Barbieri (2002) and Oneal & Russett (1999). The former excludes many missing observations, where the latter attributes them to zero. The above analysis treats these values as missing. Using Gleditsch's expanded data I created Barbieri's salience, symmetry, and interdependence measures (based on trade share) as well as Oneal & Russett's less dependent and more dependent variables, which are described in the text. This increases the sample size to nearly 280,000. I reran BMA on this data set and the findings (Tables VI and VII) are similar to those of the original manuscript. Neither author's trade measures are included in the models of conflict. The primary difference is that fewer models are supported by the data.

[Tables VI and VII about here]

Conclusion

Previously there has been uncertainty with respect to the relationship between trade and interstate conflict. Three theories have been advanced in international relations that suggest there is either no relation, a positive relation, or a negative relation.

Furthermore researchers have found contradictory empirical findings with respect to trade's effect on conflict. Oneal & Russett (1999) and Barbieri's (2002) different findings display that variable selection influences the predicted effects of trade on conflict. As a result one is uncertain of the 'true' model specification and its findings.

This paper has reexamined the liberal peace using Bayesian methods of statistics. Bayesian methods offer researchers the advantage of being able to compare the relative evidence of different model specification based on the data. In the case of trade's effect on conflict eight model specifications were supported by the data. None of these models included any of the measures of trade, though each contained the measure of joint democracy. Based on these measures of trade dependence and the other variables considered in the analysis it appears that the democratic peace does not extend to a more broad liberal peace. Analysis of politically relevant pairs did not change this finding.

The estimated coefficients generated in this analysis are also important for prediction as they account for uncertainty in variable selection. The posterior mean of each variable is a weighted sum of the estimates from each of the models selected, with weights given by each model's posterior model probability. Estimated coefficients from Bayesian model averaging have been shown by Madigan & Raftery (1994) to provide on average better out of sample predictive ability than results based on a single model specification.

Bayesian model averaging, as discussed above, provides a way in which researchers can deal with variable selection and model specification when their choice is uncertain and it allows them to incorporate this uncertainty into their estimates and predictions. The limitations of Bayesian model averaging include the subjective selection of priors as well as the choice of candidate variables to include in the models.   Further research in Bayesian statistics is necessary to determine methods of choosing priors. In addition researchers examining the effects of trade dependence on conflict need to consider alternative measures that perhaps better capture the effects of vulnerability and openness, which trade dependence is said to create. Such measures may indicate that the liberal peace does exist. For now though it appears that neither Barbieri or Oneal & Russett's measures influences conflict.

Notes

*I would like to thank Han Dorussen, Steven Durlauf, Jon Pevehouse, and several anonymous referees for comments and suggestions on earlier versions of this article. Correspondence: cullen.goenner@und.nodak.edu. The data used in this article can be obtained from http://www.business.und.edu/goenner/research/data.htm.

[1] Barbieri & Schneider (1999) and Mansfield & Pollins (2001) provide a review of the empirical literature. See also Schneider, Barbieri, & Gleditsch (2003) and Mansfield & Pollins (2003) for a more broad discussion.

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[8] Barbieri's (2002) measure of *JNTDEM* is rescaled by dividing by 4 so as to range from 0 to 100, rather than 0 to 400.

[9] The major powers throughout the period examined are the USA, China, USSR, UK and France.

[10] Oneal & Russett's (1999) data are available online at http://www.yale.edu/unsy/democ/democ1.htm. Barbieri's (2002) trade data are available online at http://www.vanderbilt.edu/psci/barbieri/Barbieribookdata.zip

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Table I: Logistic Regression Results from Alternative Models of the Onset of Militarized Disputes, 1950-1992

	Barbieri's Model		Oneal and Russett's Model	
Independent Variable	Coefficient	Std. Error	Coefficient	Std. Error
Allies	-0.2903*	0.0945	-0.4212*	0.1002
Capability Ratio	-0.0629**	0.0352	-0.1238*	0.0357
Joint Democracy	-0.0036*	0.0004	-0.0033*	0.0004
Contiguity	2.7018*	0.1041	2.2390*	0.1159
Peace Year 1	-0.2922*	0.0166	-0.2826*	0.0167
Peace Year 2	0.2787*	0.0371	0.2684*	0.0372
Peace Year 3	0.0432	0.0498	0.0424	0.0500
Peace Year 4	0.0782	0.0625	0.0813	0.0628
Partner Salience	7.3908*	1.8214		
Partner Symmetry	-1.5414*	0.5100		
Partner Interdependence	0.0323*	0.0098		
Constant	-2.0053*	0.5451	-0.5099	0.3729
Lower Dependence			-20.8506	13.9129
Higher Dependence			0.9947	1.4293
Distance			-0.3860*	0.0462
Major Dyads			1.1634*	0.1125
Log likelihood	-2741.67		-2686.55	
N	107,339		107,339	

*p≤.01, **p≤.1

Table II: Models Chosen by BMA and their Posterior Model Probability

JntDem	Distance	Contig	MajDyd	PY1	PY2	Allies	CapRat	PY3	PY4	PMP
X	X	X	X	X	X	X				.41
X	X	X	X	X	X	X	X			.34
X	X	X	X	X	X	X			X	.07
X	X	X	X	X	X	X	X		X	.06
X	X	X	X	X	X	X		X		.04
X	X	X	X	X	X	X	X	X		.03
X	X	X	X	X	X					.02
X	X	X	X	X	X		X			.02

Table III: Results of BMA Applied to Barbieri (2002) and Oneal and Russett's (1999) Regressors

Independent Variable	Bayesian Model Averaging		
	Mean β/D	St Dev β/D	Pr (β≠0/D) %
Distance	-0.3804	0.0478	100
Joint Democracy	-0.0034	0.0004	100
Contiguity	2.2451	0.1172	100
Major Dyads	1.0694	0.1262	100
Peace Year 1	-0.3010	0.0166	100
Peace Year 2	0.3203	0.0324	100
Constant	-0.6521	0.3842	100
Allies	-0.3938	0.1290	95.6
Capability Ratio	-0.0489	0.0589	44.6
Peace Year 4	0.0158	0.0437	12.9
Peace Year 3	0.0072	0.0264	7.9
Lower Dependence*	---	---	0
Higher Dependence*	---	---	0
Partner Salience*	---	---	0
Partner Symmetry*	---	---	0
Partner Interdependence*	---	---	0

*These variables were not included in the models that were supported by the data.

Table IV: Models Chosen by BMA and their Posterior Model Probability using 'Politically Relevant' Dyads.

JntDem	CapRat	Contig	Allies	Distance	PY1	PY2	PMP
X	X	X	X		X	X	.49
X	X	X	X	X	X	X	.36
X	X	X			X	X	.15

Table V: Results of BMA Applied to Barbieri (2002) and Oneal and Russett's (1999) Regressors using 'Politically Relevant' Dyads, ie either Contiguous or Containing at Least One Major Power.

	Bayesian Model Averaging		
Independent Variable	Mean β/D	St Dev β/D	Pr (β≠0/D) %
Capability Ratio	-0.1624	0.0367	100
Joint Democracy	-0.0026	0.0004	100
Contiguity	1.0061	0.1569	100
Peace Year 1	-0.2836	0.0158	100
Peace Year 2	0.2762	0.0239	100
Constant	-1.1982	0.6100	100
Allies	-0.3266	0.1712	85
Distance	-0.0527	0.0758	36
Lower Dependence*	---	---	0
Higher Dependence*	---	---	0
Major Dyads	---	---	0
Peace Year 3*	---	---	0
Peace Year 4*	---	---	0
Partner Salience*	---	---	0
Partner Symmetry*	---	---	0
Partner Interdependence*	---	---	0

*These variables were not included in the models that were supported by the data.

Table VI: Models Chosen by BMA and their Posterior Model Probability using Gleditsch's (2002) Trade Data.

JntDem	Distance	Contig	MajDyd	PY1	PY2	Allies	CapRat	PY4	PMP
X	X	X	X	X	X	X	X		.87
X	X	X	X	X	X	X	X	X	.13

Table VII: Results of BMA Applied to Barbieri (2002) and Oneal and Russett's (1999) Regressors using Gleditsch's (2002) Trade Data.

	Bayesian Model Averaging		
Independent Variable	Mean β/D	St Dev β/D	Pr (β≠0/D) %
Distance	-0.5408	0.0326	100
Joint Democracy	-0.0035	0.0003	100
Contiguity	2.3603	0.0837	100
Major Dyads	1.8678	0.0786	100
Peace Year 1	-0.2794	0.0112	100
Peace Year 2	0.3087	0.0183	100
Constant	0.2133	0.2634	100
Allies	-0.5517	0.0764	100
Capability Ratio	-0.2211	0.0238	100
Peace Year 4	0.0128	0.0348	13.2
Peace Year 3	---	---	0
Lower Dependence*	---	---	0
Higher Dependence*	---	---	0
Partner Salience*	---	---	0
Partner Symmetry*	---	---	0
Partner Interdependence*	---	---	0

*These variables were not included in the models that were supported by the data.

Biographical Statement

CULLEN F. GOENNER, b. 1973, PhD in Economics (University of Wisconsin-Madison, 2001); Assistant Professor, University of North Dakota (2001-). Current main interest: model specification and international trade.

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