PROJECT SUMMARY

Testing systematic predictions about future events against observed outcomes is generally seen as the most stringent validity check of statistical and theoretical models. Yet, political scientists rarely make predictions about the future. Empirical models are seldom applied to out-of-sample data and are even more rarely used to make predictions about future outcomes. Instead, researchers typically focus on developing and validating theories that explain past events.

In part, this results from the fact that it is difficult to make accurate predictions about complex social phenomena. However, research in political science could gain immensely in its policy relevance if predictions were more common and more accurate. Improved forecasting of important political events would make research more germane to policymakers and the general public who may be less interested in explaining the past than anticipating and altering the future. From a scientific standpoint, greater attention to forecasting would facilitate stringent validation of theoretical and statistical models since truly causal models should perform better in out-of-sample forecasting.

We propose to extend a promising statistical method – ensemble Bayesian model averaging (EBMA) – and to develop software that will aid scholars across disciplines to make more accurate forecasts. This project builds on work in the fields of meteorology and statistics to (1) extend the method for application to a wider array of outcomes (e.g., binary data), (2) provide freely available software that implements both maximum likelihood and Bayesian estimation techniques, and (3) publish papers that provide accessible explanations of the method and social science applications.

In essence, EBMA improves prediction by pooling information from multiple forecast models to generate ensemble predictions similar to a weighted average of component forecasts. The weight assigned to each forecast is calibrated via its performance in some training period. The aim is not to choose some "best" model, but rather to incorporate the insights and knowledge implicit in various forecasting efforts via statistical postprocessing. These component models can be diverse. They need not share covariates, functional forms, or error structures. Indeed, the components may not even be statistical models, but may be predictions generated by agent-based models, stochastic simulations, or subject-matter experts. In practice, the method provides superior predictive power relative to any single component and reduces the likelihood of dramatic miss-predictions as it is reliant on any one data source or methodology.

Intellectual merit: This project will address several substantive questions in political science with a focus on the field of international relations, where policymakers have a particular demand for improved forecasting. We will also further develop statistical techniques that will improve the capabilities of researchers across disciplines to produce more accurate forecasts of future events. The methodological advancement made in this project will be available to the larger scholarly community and influence research agendas in multiple fields. EBMA has received considerable attention in the fields of statistics, meteorology, and (to a lesser extent) economics. Yet, it has not been advanced in the methodological directions we are proposing here. Additionally, our work will make EBMA available to a wider audience of researchers across the physical and social sciences. This is particularly important as existing research projects and software packages are narrowly tailored to the needs of weather forecasting.

Broader impacts: The principal investigators are active members of the research community at the intersection of statistics and the social sciences. Their work is widely read in political science and other disciplines. Further, at least two graduate student in political science will be included in the research and will gain experience in large-scale research projects.

Project Description

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1. Dynamic forecasting in political science

Although forecasting remains a rare exercise in political science, there are an increasing number of exceptions. In most cases, "forecasts" are conceptualized as an exercise in which the predicted values of a dependent variable are calculated based on a specific statistical model and then compared with observed values (e.g., Hildebrand, Laing and Rosenthal 1976). In many instances, this reduces to an analysis of residuals. In others, the focus is on randomly selecting subsets of the data to be excluded during model development for cross-validation. However, there is also a more limited tradition of making true forecasts about events that have not yet occurred.

An early proponent of using statistical models to make predictions in the realm of international relations (IR) was Stephen Andriole (Andriole and Young 1977). In 1978, a volume edited by Nazli Choucri and Thomas Robinson provided an overview of the then current work in forecasting in IR. Much of this work was done in the context of policy-oriented research for the U.S. government during the Vietnam War. Subsequently, there were a variety of efforts to create or evaluate forecasts of international conflict including Freeman and Job (1979), Singer and Wallace (1979), and Vincent (1980). In addition, a few efforts began to generate forecasts of domestic conflict (e.g., Gurr and Lichbach 1986). Recent years, however, have witnessed increasing interest in prediction across a wide array of contexts in IR.[1] The 2011 special issue of *Conflict Management and Peace Science* on prediction in the field of IR exemplifies this growing emphasis on forecasting (c.f., Schneider, Gleditsch and Carey 2011; Bueno de Mesquita 2011; Brandt, Freeman and Schrodt 2011).

[1] An incomplete list of recent work would include Krause (1997), Davies and Gurr (1998), Pevehouse and Goldstein (1999), Schrodt and Gerner (2000), King and Zeng (2001), O'Brien (2002), Bueno de Mesquita (2002), Fearon and Laitin (2003), de Marchi, Gelpi and Grynaviski (2004), Enders and Sandler (2005), Leblang and Satyanath (2006), Ward, Siverson and Cao (2007), Brandt, Colaresi and Freeman (2008), Bennett and Stam (2009), and Gleditsch and Ward (2010). A summary of classified efforts is reported in Feder (2002). An overview of some of the historical efforts along with a description of current thinking about forecasting and decision-support is given by O'Brien (2010).

Outside of IR, forecasting in political science has largely taken place in the context of election research. In the 1990s, scholars of U.S. politics began publishing predictions of presidential elections (Campbell and Wink 1990; Campbell 1992). These efforts were anticipated by the efforts of several economists, most notably the forecast established by Ray C. Fair (1978). As we discuss below, predicting U.S. presidential and congressional elections has since developed into a regular exercise. Moreover, researchers have begun to forecast election outcomes in France (e.g., Jerome, Jerome and Lewis-Beck 1999) and the United Kingdom (e.g., Whiteley 2005). Lewis-Beck (2005) provides a more in-depth discussion of election forecasting in a comparative context.

While efforts to predict future outcomes remain uncommon, research that combines multiple forecasts are nearly non-existant. To our knowledge, the only non-IR example is the PollyVote project (c.f. Graefe et al. 2010), which combines multiple predictions using simple averages to forecast U.S. presidential elections.

EBMA is a statistical approach that promises to improve prediction of complex social outcomes and build upon the increased interest in generating political forecasts. In essence, EBMA improves prediction by pooling information from multiple forecast models to generate ensemble predictions similar to a weighted average of component forecasts. The weight assigned to each forecast is calibrated via its performance in some training period. These component models can be diverse. They need not share covariates, functional forms, or error structures. Indeed, the components may not even be statistical models, but may be predictions generated by agent-based models, stochastic simulations, or subject-matter experts.

Such ensemble methods have been shown to significantly reduce prediction error in two important ways. First, ensemble predictions are usually more accurate than any individual component model. Second, they are significantly less likely to make dramatically incorrect predictions (Bates and Granger 1969; Armstrong 2001; Raftery et al. 2005). Combining forecasts not only reduces reliance on single data sources and methodologies (which lowers the likelihood of dramatic errors), but also allows for the incorporation of more information than any one theoretical or statistical model is likely to include in isolation.

2. Ensemble Bayesian model averaging

Predictive models remain underutilized, yet an increasing number of scholars have developed forecasting models for specific research domains. As the number of forecasting efforts proliferate, however, there is a growing benefit from developing methods to pool across models and methodologies to generate more accurate forecasts. Very often, specific predictive models prove to be correct only for certain subsets of observations. Moreover, stand-alone models tend to be more sensitive to unusual events or particular data issues than ensemble methods.

The research proposed here will aid the newfound emphasis on prediction by advancing recent statistical research aimed at integrating multiple predictions into a single improved forecast. In particular, we are adapting an ensemble method first developed for application to the most mature prediction models in existence – weather forecasting models. To generate predictive distributions of outcomes (e.g., temperature), weather researchers apply ensemble methods to forecasts generated from multiple models (Raftery et al. 2005). Thus, state-of-the-art ensemble forecasts aggregate multiple runs of (often multiple) weather prediction models into a single unified forecast.

The particular ensemble method we are extending for application to political outcomes is ensemble Bayesian model averaging (EBMA). First proposed by Raftery et al. (2005), EBMA pools across various forecasts while meaningfully incorporating *a priori* uncertainty about the "best" model. It assumes that no particular model or forecasting method can fully encapsulate the true data-generating process. Rather, various research teams or statistical techniques will reflect different facets of reality. EBMA collects *all* of the insights from multiple forecasting efforts in a coherent manner. The aim is not to choose a model, but rather to incorporate the insights and knowledge implicit in various forecasting efforts via statistical post-processing.

EBMA itself is an extension of the Bayesian model averaging (BMA) methodology (c.f., Madigan and Raftery 1994; Draper 1995; Raftery 1995; Hoeting et al. 1999; Clyde 2003; Raftery and Zheng 2003; Clyde and George 2004). BMA was first introduced to political science by Bartels (1997) and has been applied in a number of contexts (e.g., Bartels and Zaller 2001; Gill 2004; Imai and King 2004; Geer and Lau 2006). Montgomery and Nyhan (2010) provide a more in-depth discussion of BMA and its applications in political science.

2.1. **Mathematical intuition.** Assume we have some quantity of interest in the future to forecast, $\mathbf{y}^*$, based on previously collected training data $\mathbf{y}^T$ that is fit to K statistical models, $M_1, M_2, \ldots, M_K$. Each model, M_k, is assumed to come from the prior probability distribution $M_k \sim \pi(M_k)$, and the probability distribution function (PDF) for the training data is $p(\mathbf{y}^T|M_k)$. The outcome of interest is distributed $p(\mathbf{y}^*|M_k)$. Applying Bayes Rule, we get that

$$p(M_k|\mathbf{y}^T) = \frac{p(\mathbf{y}^T|M_k)\pi(M_k)}{\sum\limits_{k=1}^{K} p(\mathbf{y}^T|M_k)\pi(M_k)}. \tag{1}$$

and the marginal predictive PDF for y^* is

$$p(\mathbf{y}^*) = \sum_{k=1}^{K} p(\mathbf{y}^*|M_k)p(M_k|\mathbf{y}^T). \tag{2}$$

The BMA PDF (2) can be viewed as the weighted average of the component PDFs where the weights are determined by each model's performance within the training data. Likewise, we can simply make a deterministic estimate using the weighted predictions of the components, denoted

$$E(\mathbf{y}^*) = \sum_{k=1}^{K} E(\mathbf{y}^*|M_k)p(M_k|\mathbf{y}^T). \tag{3}$$

2.2. **EBMA for dynamic settings.** We now turn to applying this basic BMA technology to prediction in a dynamic setting. In generating predictions of important events (e.g., domestic crises or international disputes), the task is to first build a statistical model for some set of observations S in time periods T, which we refer to as the training period.[2] Using the same statistical model (or general technique in the case of subject-expert predictions), we then generate forecasts, $\mathbf{f}_k$, for observations S in future time periods T^*.

Let us assume, for example, that we have K models forecasting insurgencies in a set of countries S. Each component forecast, $\mathbf{f}_k$, is associated with a component PDF, $g_k(\mathbf{y}|\mathbf{f}_k)$, which may be the original predictive PDF from the forecast model or a bias-corrected forecast. These components are the conditional PDFs of outcome $\mathbf{y}$ given the kth forecast, $\mathbf{f}_k$ assuming that $P(M_k|\mathbf{y}) \equiv w_k = 1$, or that the posterior odds of model k is unity.

[2]Sloughter et al. (2007) make predictions for only one future time period, and use only a subset of past time-periods (they recommend 30) in their training data. Thus, predictions are made sequentially with the entire EBMA procedure being re-calculated for each future event as observations are moved from the out-of-sample period T^* into the training set T. Another alternative is to simply divide *all* the data into discrete training and test periods for the entire procedure. We use both approaches in our examples below.

The EBMA PDF is then a finite mixture of the K component forecasts, denoted

$$p(\mathbf{y}|\mathbf{f}_1, \ldots, \mathbf{f}_K) = \sum_{k=1}^{K} w_k g_k(\mathbf{y}|\mathbf{f}_k), \tag{4}$$

where the weight, w_k, is based on forecast k's relative predictive performance in the training period T. The w_k's $\in [0, 1]$ are probabilities and $\sum_{k=1}^{K} w_k = 1$. The specific PDF of for an out-of-sample event, y_{st^*}, is therefore

$$p(y_{st^*}|f_{1st^*}, \ldots, f_{Kst^*}) = \sum_{k=1}^{K} w_k g_k(y_{st^*}|f_{kst^*}). \tag{5}$$

2.3. **EBMA for normally distributed outcomes.** When forecasting outcomes that are distributed according to the normal distribution, Raftery et al. (2005) propose approximating the conditional PDF as a normal distribution centered at a linear transformation of the individual forecast, $g_k(\mathbf{y}|\mathbf{f}_k) = N(a_{k0} + a_{k1}\mathbf{f}_k, \sigma^2)$. Using (4) above, the EBMA PDF is then

$$p(\mathbf{y}|\mathbf{f}_1, \ldots, \mathbf{f}_K) = \sum_{k=1}^{K} w_k N(a_{k0} + a_{k1}\mathbf{f}_k, \sigma^2). \tag{6}$$

2.4. **The dichotomous outcome model.** Past work on EBMA does not apply directly to the prediction of many political events because the assumed PDFs are normal, Poisson, or gamma. In many settings (e.g., international conflicts), the data are not sufficiently fine-grained to justify these distributional assumptions. Usually, the outcomes of interest are dichotomous indicators for whether an event (e.g., civil war) has occurred in a given time period and country. Thus, none of the distributional assumptions used in past work are appropriate in this context. Fortunately, it is a straightforward extension of Sloughter et al. (2007) and Sloughter, Gneiting and Raftery (2010) to deal appropriately with binary outcomes.

We follow Sloughter et al. (2007) and Hamill, Whitaker and Wei (2004) in using logistic regression after a power transformation of the forecast to reduce prediction bias. For notational ease, we assume that $\mathbf{f}_k$ is the forecast after the adjustment for bias reduction. Therefore, let $\mathbf{f}'_k \in [0, 1]$ be the forecast on the predicted probability scale and

$$\mathbf{f}_k = \left[(1 + \text{logit}(\mathbf{f}'_k))^{1/b} - 1\right] I\left[\mathbf{f}'_k > \frac{1}{2}\right] - \left[(1 + \text{logit}(|\mathbf{f}'_k|))^{1/b} - 1\right] I\left[\mathbf{f}'_k < \frac{1}{2}\right], \tag{7}$$

where $I[.]$ is the general indicator function. Hamill, Whitaker and Wei (2004) recommend setting $b = 4$, while Sloughter et al. (2007) use $b = 3$. We found that $b = 4$ works best in the examples below, but other analysts may try alternative specifications. This transformation dampens the effect of extreme observations and reduces over-fitting.

The logistic model for the outcome variables is

$$\text{logit } P(\mathbf{y} = 1|\mathbf{f}_k) \equiv \log \frac{P(\mathbf{y} = 1|\mathbf{f}_k)}{P(\mathbf{y} = 0|\mathbf{f}_k)} = a_{k0} + a_{k1}\mathbf{f}_k. \tag{8}$$

The conditional PDF of some within-sample event, given the forecast f_{kst} and the assumption that k is the true model, can be written

$$g_k(y_{st}|f_{kst}) = P(y_{st} = 1|f_{kst})I[y_{st} = 1] + P(y_{st} = 0|f_{kst})I[y_{st} = 0]. \tag{9}$$

Applying this to (4), the PDF of the final EBMA model for y_{st} is

$$p(y_{st}|f_{1st}, f_{2st}, \ldots, f_{Kst}) = \sum_{k=1}^{K} w_k[P(y_{st} = 1|f_{kst})I[y_{st} = 1] + P(y_{st} = 0|f_{kst})I[y_{st} = 0]]. \tag{10}$$

2.5. **Parameter estimation by maximum likelihood and EM algorithm.** Parameter estimation is conducted using only the data from the training period T. The parameters a_{0k} and a_{1k} are specific to each individual component model. For model k, these parameters can be estimated as traditional linear models where $\mathbf{y}$ is the dependent variable with a constant and the covariate $\mathbf{f}_k$.

The difficulty is in estimating the weighting parameters, $w_k \; \forall \; k \in [1, 2, \ldots, K]$. One approach we propose to implement with NSF support is to place priors on all parameters and conduct a fully Bayesian analysis with Markov chain Monte Carlo (MCMC) techniques (c.f. Vrugt, Diks and Clark 2008). For the moment, however, we have followed Raftery et al. (2005) and Sloughter et al. (2007) in using maximum likelihood methods.

With standard independence assumptions, the log-likelihood for the model weights is

$$\ell(w_1, \ldots, w_K|a_{01}, \ldots, a_{0K}; a_{11}, \ldots, a_{1K}) = \sum_{s,t} \log p(y_{st}|f_{1st}, \ldots, f_{Kst}). \tag{11}$$

where the summation is over values of s and t that index all observations in the training time period, and $p(y_{st}|f_{1st}, \ldots, f_{Kst})$ is given by (10). The log-likelihood function cannot be maximized analytically, but Raftery et al. (2005) and Sloughter et al. (2007) suggest using the expectation-maximization (EM) algorithm. We introduce the unobserved quantities z_{kst}, which represent the posterior probability for model k for observation y_{st}. The E step involves calculating estimates for these unobserved quantities using the formula

$$\hat{z}_{kst}^{(j+1)} = \frac{\hat{w}_k^{(j)} p^{(j)}(y_{st}|f_{kst})}{\sum_{k=1}^{K} \hat{w}_k^{(j)} p^{(j)}(y_{st}|f_{kst})}, \tag{12}$$

where the superscript j refers to the jth iteration of the EM algorithm.

It follows that $w_k^{(j)}$ is the estimate of w_k in the jth iteration and $p^{(j)}(.)$ is shown in (10). Assuming these estimates of z_{kst} are correct, it is then straightforward to derive the maximizing value for the model weights. Thus, the M step estimates these as $\hat{w}_k^{(j+1)} = \frac{1}{n}\sum_{s,t} \hat{z}_{kst}^{(j+1)}$, where n represents the number of observations in the training dataset. The E and M steps are iterated until the improvement in the log-likelihood is no larger than some pre-defined tolerance.[3]

2.6. **Ensemble prediction.** With these parameter estimates, it is now possible to generate ensemble forecasts. If our forecasts, $\mathbf{f}_k$, are generated from a statistical model, we now generate a new prediction, f_{kst^*}, from the previously fitted models. For convenience, let $\hat{\mathbf{a}}_k \equiv (\hat{a}_{k0}, \hat{a}_{k1})$. For some dichotomous observation in country $s \in S$ in the out-of-sample period $t^* \in T^*$, we can see that

$$P(y_{st^*} = 1|f_{1st^*}, \ldots, f_{Kst^*}; \hat{\mathbf{a}}_1, \ldots, \hat{\mathbf{a}}_K; \hat{w}_1, \ldots, \hat{w}_K) = \sum_{k=1}^{K} \hat{w}_k \text{logit}^{-1} \left(\hat{a}_{k0} + \hat{a}_{k1} f_{kst^*} \right). \tag{13}$$

[3]Although the log-likelihood will increase after each iteration of the algorithm, convergence is only guaranteed to a local maximum of the likelihood function. Convergence to the global maximum is not assured, and the model may be sensitive to initial conditions. As part of our proposed research, we will explore these convergence issues more fully with special attention paid to comparison with fully Bayesian implementations. In the examples below, we begin with the assumption that all models are equally likely, $w_k = \frac{1}{K} \; \forall \; k \in [1, \ldots, K]$.

3. Empirical applications

3.1. **Application to insurgency forecasting.** Our first example applies the EBMA method to data collected for the Integrated Crisis Early Warning Systems (ICEWS) project sponsored by the Defense Advanced Research Projects Agency (DARPA). The task of the ICEWS project is train models on data (focusing on five outcomes of interest) for 29 countries for every month from 1997 through the present and to then make predictions about expected crisis events over the subsequent three months.[4] For purposes of demonstration, we focus on only predicting violent insurgency.

The bulk of the data for the ICEWS project is gleaned from natural language processing of a continuously updated harvest of news stories (primarily taken from Lexus/Nexus and Factiva archives). These are digested with a version of the TABARI processor for events developed by Philip Schrodt and colleagues in the context of the Event Data Project (see `http://eventdata.psu.edu/` for more details). These data are augmented with a variety of covariates including: country-level attributes (coded on a monthly or yearly basis) from the Polity and World Bank datasets, information about election cycles (if any), events in neighboring countries, and the length of shared borders with neighboring countries.

3.1.1. *Component Models.* In the remainder of this subsection, we apply EBMA to make predictions for the occurrence of insurgency in these 29 countries. We estimate three exemplar statistical models using data for the in-sample period ranging from January 1999 to December 2008 and fit an EBMA model. We then make out-of-sample forecasts for the period from January 2009 to December 2010 for the component and EBMA models. To provide variation in the complexity (as well as accuracy) of the components, we included the following models.

- **SAE**: This is one model developed as part of the ICEWS project and was designed by Strategic Analysis Enterprises. It is specified as a simple logistic model including 27 different independent variables.[5] All of the variables are taken from the ICEWS event-stream data.
- **GLM**: For the purposes of demonstrating the performance of EBMA, we estimated a crude logistic model that includes only *population size* and *GDP growth* (both lagged three months).
- **LMER**: This is a generalized linear mixed effects model using a logistic link function and including random country-level intercepts as well as a random country-level coefficient for *per capital GDP*. The list of covariates includes: *population size*, the *executive constraint* and *competitiveness of participation* variables from the Polity IV dataset (Marshall, Jaggers and Gurr 2009), *proximity to election*,[6] and a *spatial lag* that reflects recent occurrences of insurgencies in the countries' geographic neighbors.[7]

3.1.2. *Results.* Table 1 shows the EBMA model parameters as well as fit statistics associated with the individual component models and the EBMA predictions for the in-sample time period. The first column shows the weights that the EBMA model assigned to each component. As can be seen, the GLM model is effectively excluded, while the SAE model carries the greatest weight followed by the LMER model. The constant term associated with each component corresponds to the term

[4]The twenty-nine countries are Australia, Bangladesh, Bhutan, Cambodia, China, Comoros, Fiji, India, Indonesia, Japan, Laos, Madagascar, Malaysia, Mauritius, Mongolia, Myanmar, Nepal, New Zealand, North Korea, Papua New Guinea, Philippines, Russia, Singapore, Solomon Islands, South Korea, Sri Lanka, Taiwan, Thailand, and Vietnam. This set is not a random sample, but rather constitutes the countries of population greater than $500,000$ that are in the area of responsibility of the US Pacific Command.

[5]See `strategicanalysisenterprises.com` for more details.

[6]This is calculated as the number of days to the next or from the last election, whichever is closer.

[7]Geographical proximity is measured in terms of the length of the shared border between the two countries.

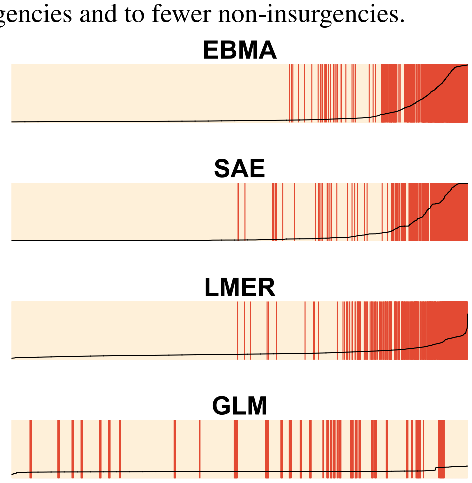
a_{k0} in (8), while the predictor corresponds to a_{k1}. The other columns in Table 1 are fit statistics. AUC is the area under the Receiver-Operating Characteristic (ROC) curve. The advantage of using ROC curves is that it evaluates forecasts in a way that is less dependent on an arbitrary cutoff point. A value of 1 would mean that all observations were predicted correctly at all possible cutoff points (King and Zeng 2001).

TABLE 1. In-sample results. The table shows estimated model weights, parameters, and fit statistics for the EBMA deterministic forecast and all component forecasts of insurgency in 29 countries of the Pacific Rim. EBMA equals or outperforms any single model on all measures.

	Weight	Constant	Predictor	AUC	PRE	Brier	% Correct
SAE	0.57	0.04	7.46	0.96	0.48	0.04	94.11
LMER	0.43	6.08	28.25	0.96	0.01	0.07	88.79
GLM	0.00	0.57	8.16	0.65	0.00	0.10	88.65
EBMA				0.97	0.55	0.04	94.94

n=3,480

FIGURE 1. Separation plots for in-sample predictions of the ICEWS data (n=3,480). For each model, observations are shown from left to right in order of increasing predicted probability of insurgency (shown as the black line). Observations where insurgency actually occurred are shown in red. EBMA outperforms all component models in assigning high predicted probabilities to more observed insurgencies and to fewer non-insurgencies.



We compare the models using three additional metrics. The proportional reduction in error (PRE) is the percentage increase of correctly predicted observations relative to some pre-defined base model. In this case, the base model is predicting "no insurgencies" for all observations. Insurgencies are relatively rare events. Thus, predicting a zero for all observations leads to an 89% correct prediction rate. The Brier score is the average squared deviation of the predicted probability from the true event (0 or 1). Thus, a lower score corresponds to higher forecast accuracy (Brier 1950). Finally, we calculate the percentage of observations that each model would predict correctly using a 0.5 threshold on the predicted probability scale.

There are two aspects of Table 1 that are important to note. First, the EBMA model does at least as well (and usually better) than all of the component models on each our model fit statistics. The EBMA model has the highest AUC, PRE, and % correct. In addition, it is tied for the lowest Brier score with the SAE model. Second, in this example the EBMA procedure assigns probability weights to each model according to their in-sample performance. The largest weight (0.57) is assigned to the SAE model, which appears to be the best (or tied for the best) component as measured by all the fit statistics. Meanwhile, the smallest weight (0.00) is assigned to the rudimentary GLM model.

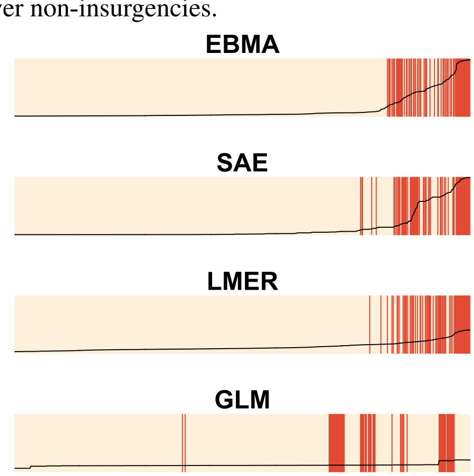
TABLE 2. Out-of-sample results. The table shows fit statistics for the EBMA deterministic forecast and all component model forecasts of insurgency in 29 countries of the Pacific Rim. EBMA equals or outperforms any single model on most measures.

	AUC	PRE	Brier	% Correct
SAE	0.96	0.04	0.06	89.80
LMER	0.97	0.00	0.07	89.37
GLM	0.84	0.00	0.09	89.37
EBMA	0.96	0.18	0.05	91.24

n=696

Figure 1 shows separation plots for the EBMA model and the individual components (Greenhill, Ward and Sacks 2011). In each plot, the observations are ordered from left to right by increasing predicted probabilities of insurgency (as predicted by the particular model). The black line corresponds to the predicted probability produced by the relevant model for each observation and actual occurrences of insurgencies are colored red. Figure 1 shows visually that the GLM model performs very poorly, whereas of the SAE model is the best component. More importantly, the overall best performance is associated with the EBMA forecast. The separation plots show that it produces few false positives and even fewer false negatives than any of the component models.

FIGURE 2. Separation plots for out-of-sample predictions of the ICEWS data (n=696). For each model, observations are shown from left to right in order of increasing predicted probability (shown as the black line). Observations where insurgency actually occurred are shown in red. EBMA outperforms all component models in assigning high predicted probabilities to more observed insurgencies and to fewer non-insurgencies.



The more interesting evaluation of the EBMA method is its out-of-sample predictive power. Table 2 shows fit statistics for the individual components as well as the EBMA forecasts for observations in the 24 months following the training period. While the EBMA model has a marginally smaller area under the ROC curve than the LMER models, it outperforms all component models on the other metrics. In particular, the EBMA model has the highest PRE at 0.18. Since it is possible to predict 89.22% of these observations correctly by forecasting no insurgency, an 18% reduction of error relative to the baseline model is quite substantial.

Figure 2 shows the separation plots for the components as well as the EBMA forecasts for the out-of-sample data. The EBMA model performs better than any of the individual components, with high predicted probabilities for most observed insurgencies. Taking both the fit statistics and the visual evidence together, we can conclude that the EBMA model leads to a substantial improvement in out-of-sample forecasts relative to its components.

3.2. **Application to US presidential election forecasts.** For the past several U.S. election cycles, a number of research teams have developed forecasting models and published their predictions in advance of Election Day. For example, before the 2008 election, a symposium of forecasts was published in *PS: Political Science and Politics* with forecasts of presidential and congressional vote shares developed by Campbell (2008), Norpoth (2008), Lewis-Beck and Tien (2008), Abramowitz (2008), Erikson and Wlezien (2008), Holbrook (2008), Lockerbie (2008) and Cuzàn and Bundrick (2008). Responses to the forecast were published in a subsequent issue. Earlier, in 1999, an entire issue of the *International Journal of Forecasting* was dedicated to the task of predicting presidential elections (Brown and Chappell 1999). Predicting presidential elections has also drawn the attention of economists seeking to understand the relationship between economic fundamentals and political outcomes. Two prominent examples include work by Ray Fair (2010) and Douglas Hibbs (2000).

3.2.1. *Component Models.* In the rest of this subsection, we replicate several of these models and demonstrate the usefulness of the EBMA methodology for improving the prediction of single important events. We include six of the most widely cited presidential forecasting models.

- **Campbell**: Campbell's "Trial-Heat and Economy Model" (Campbell 2008)
- **Lewis-Beck/Tien**: Lewis-Beck and Tien's "Jobs Model Forecast" (Lewis-Beck and Tien 2008)
- **Erikson/Wlezien**: Erikson and Wlezien's "Leading Economic Indicators and Poll" forecast[8]
- **Fair**: Fair's presidential vote-share model[9]
- **Hibbs**: Hibbs' "Bread and Peace Model" (Hibbs 2000)
- **Abramowitz**: The "Time-for-Change Model" created by Abramowitz (2008)

With the exception of the Hibbs forecast, the models are simple linear regressions. The dependent variable is the share of the two-party vote received by the incumbent-party candidate.[10]

3.2.2. *Results.* Rather than selecting a single training period (as in the insurgency analysis) we generate sequential predictions. For each year from 1976 to 2008, we use all available prior data to fit the component models.[11] We then fit the EBMA model using the components' in-sample performances for election years beginning with 1952 (the year when all models begin generating predictions). For example, to generate predictions for the 1988 election, we used the in-sample performance of each component for the 1952-1984 period to estimate model weights.[12]

Table 3 provides exemplar results for the 2004 and 2008 elections. Table 3 shows the weights assigned to each model as well as the in-sample root mean squared error (RMSE) and mean absolute error (MAE) for the components and the EBMA forecasts. The table also shows the out-of-sample prediction errors, calculated as $y_{predicted} - y_{observed}$, for each forecast.

The example results in Table 3 illustrate three important points. First, the EBMA model again does better than any individual component on in-sample measures of model fit (i.e., RMSE and

[8]We replicated Column 2 in Table 2 from Erikson and Wlezien (2008).

[9]The model here replicates Equation 1 in Fair (2010).

[10]The data to replicate the models by Abramowitz (2008), Campbell (2008), Erikson and Wlezien (2008), and Lewis-Beck and Tien (2008) were provided in personal correspondence with the respective authors. The remaining data were downloaded from the web sites of Ray C. Fair and Douglas Hibbs .

[11]For example, the Fair model uses data for election results beginning in 1916 while the Abramowitz model begins with data from the 1952 election.

[12]Results in this section were computed using modifications of the 'ensembleBMA' package (Fraley et al. 2010, 2011). Because of the paucity of data, we did not apply any bias correction to these forecasts. Thus, the predictor and constant, denoted a_{0k} and a_{1k} above, are constrained to zero and one respectively.

TABLE 3. Prediction errors, model weights, and in-sample fit statistics for component and EBMA forecasts of the 2004 and 2008 elections. Models are sequentially fit using all prior elections. The EBMA model does better than all components on in-sample fit statistics. Although it does not necessarily make the most accurate prediction for any given year, it is less likely to make dramatic forecasting errors.

	2004 Election				*2008 Election*			
	Weights	RMSE	MAE	Pred. Error	Weights	RMSE	MAE	Pred. Error
Campbell	0.40	1.71	1.33	0.53	0.36	1.65	1.28	6.33
Lewis-Beck/Tien	0.00	1.67	1.42	−0.41	0.17	1.61	1.33	−2.65
Erikson/Wlezien	0.00	2.67	2.06	4.76	0.17	2.81	2.18	−0.14
Fair	0.48	2.07	1.47	4.82	0.00	2.22	1.80	−2.02
Hibbs	0.12	1.95	1.38	1.54	0.25	1.92	1.38	−1.39
Abramowitz	0.00	1.50	1.18	2.20	0.06	1.53	1.26	−2.37
EBMA		1.29	1.01	2.08		1.30	1.01	−0.53

MAE). Second, these results demonstrate that EBMA is not guaranteed to generate the most accurate prediction for any single observation. Thus, in each year some component models come closer to predicting the actual outcome. However, the EBMA forecasts will very rarely provide egregiously wrong predictions (e.g., the Campbell model in 2008 and the Fair model in 2004) since it borrows predictions from multiple components. Moreover, as we show below, in the aggregate the EBMA model tends to provide the best forecast over time.

Third, Table 3 shows it is clear that there is not as clean a relationship between in-sample model performance and model weights as in the insurgency example. For instance, the weight for the Abramowitz model in 2008 is 0.06 even though it has the lowest RMSE and MAE of any component. The diminished relationship between in-sample performance and weight is a result of high in-sample correlations between forecasts. For instance, fitted values for the Abramowitz model are correlated at 0.94 with the Campbell model and at 0.96 with the Lewis-Beck/Tien model. Thus, conditioned on knowing these forecasts, the Abramowitz component provides limited information.

With the 2004 and 2008 examples in mind, we now turn to the relative out-of-sample performance of the EBMA and component forecasts across the entire 1976-2008 period. Table 4 shows the out-of-sample RMSE and MAE statistics as well as the percentage of observations that fall within the 67% and 95% predictive intervals for each. For our purposes here, the main result in Table 4 is that the EBMA model again outperforms all components. The first two columns show this to be true in terms of predicted error (RMSE and MAE).

In addition, the coverage statistics demonstrate better calibration of EBMA forecasts relative to its component models. For instance, the observed outcome falls within the 67% predictive interval for the Abramowitz model only three out of nine times, while it covers the observed values eight out of nine times for the Lewis-Beck/Tien model. Meanwhile, the EBMA 90% an 67% predictive intervals are nearly perfectly calibrated.

In a well-calibrated forecasting model, out-of-sample outcomes should fall within predictive intervals at a rate corresponding to their size. For instance, the goal is for two-thirds of all out-of-sample observations to fall within of their respective 67% predictive intervals. Poorly calibrated models will tend to be produce predictive intervals that are either too narrow, generating inaccurate predictions, or too large, generating predictions that are accurate but too vague to be useful. For example, two of the most accurate forecasts, the Lewis-Beck/Tien and Erikson/Wlezien models,

TABLE 4. Fit statistics and observed coverage probabilities for sequentially generated out-of-sample predictions of presidential elections from 1976-2008. EBMA outperforms its component models on all metrics.

			Coverage	
	RMSE	MAE	67%	90%
EBMA	1.72	1.47	0.67	0.89
Campbell	2.74	1.99	0.67	0.78
Lewis-Beck/Tien	2.27	1.82	0.89	1.00
Erikson/Wlezien	2.88	2.16	0.78	1.00
Fair	4.01	3.20	0.44	0.78
Hibbs	2.81	2.24	0.44	0.78
Abramowitz	2.27	2.05	0.33	0.78

make very imprecise predictions. Thus, although they have very good coverage, it is at least partly because their estimates are so inexact. The Campbell, Abramowitz, and Hibbs models provide more reasonable predictive intervals, but are less accurate than EBMA. Meanwhile, the Fair model falls somewhere in between these two groupings.

Finally, it is worth noting an example – very noticeable in this data – of the kinds of problems that may arise when relying on a single model for making predictions. From 1952 to 2004, the Campbell model was consistently one of the strongest performers. Indeed, it made the most accurate forecast of the 2004 election. However, one of the crucial variables in this model comes from polling data measured in early September. As a result of the particularly late timing of the Republican Convention in 2008, it was the only model to forecast a victory for John McCain. By relying on a wider array of data sources and methodologies, EBMA reduces the likelihood of such large misses without completely eliminating the general insights captured by individual models that may on occasion be wide of the mark.

3.3. **Application to Supreme Court Forecasting Project.** Our final application of EBMA is a re-analysis of data from the Supreme Court Forecasting Project (Ruger et al. 2004; Martin et al. 2004).[13] This example highlights the ability of EBMA to handle forecasts generated by classification trees, subject experts, and other sources.

Throughout 2002-2003, a research team consisting of Andrew Martin, Kevin Quinn, Theodore Ruger, and Pauline Kim (henceforward MQRK) generated two sets of forecasts for every pending case. First, using data about case characteristics and justices' past voting patterns, MQRK developed classification trees to generate a binary forecasts for the expected vote of each justice on each case (voting to affirm the lower court opinion is coded as a 1). Second, MQRK recruited a team of 83 legal experts to make forecasts on particular cases in their specialty area. The list included academics, appellate attorneys, former Supreme Court clerks, and law school deans. MQRK attempted to recruit three expert forecasts for each case, although this was not possible for all cases.

The statistical model makes predictions for all 67 cases included in the MQRK analysis. Thus, we include the binary model predictions as one component forecast. However, the individual legal experts made predictions on only a handful of cases. Owing to the paucity of the data for each judge, we pooled them together and treat all of the expert opinions as part of a single forecasting

[13]Additional details about the project, replication files, as well as a complete listing of cases and expert forecasts are available at: `http://wusct.wustl.edu/index.php`.

effort. We coded the expert forecast to be the mean expert prediction. This implies that the expert forecast predicts a vote to affirm if a majority of experts polled for that case predict an affirming vote. We fit an EBMA model using all cases with docket numbers dating from 2001 (n=395) and made EBMA forecasts for the remaining 296 cases with 2002 docket numbers.

3.3.1. *Results.* Table 5 shows the component weights for the two forecasts and the out-of-sample fit statistics for the MQRK classification trees, the subject experts, and the EBMA forecast. Once again, the results show that the EBMA procedure outperforms all components (even when there are only two). In terms of AUC, Brier scores, and correct predictions, the EBMA forecast outperforms both the statistical model and the combined subject experts. In addition, EBMA scores substantially better on the PRE metric.[14]

TABLE 5. Out-of-sample results for U.S. Supreme Court example. The table shows fit statistics for the EBMA deterministic forecast and component forecasts of U.S. Supreme Court votes on cases in the 2002-2003 session with 2002 docket numbers. EBMA outperforms its component models on all metrics.

	Weight	AUC	PRE	Brier	% Correct
MQRK model	0.32	0.66	-0.02	0.29	70.56
Subject experts	0.68	0.62	0.15	0.23	75.23
EBMA forecast		0.70	0.21	0.18	77.10

n=214

There is a long-standing debate in may circles of the relative strengths and weaknesses of statistical models and subject experts for making predictions (e.g., Ascher 1979). Models that use quantifiable measurements and widely available (if sometimes crude) data to make predictions can make egregious errors in particular cases. Some cases may be decided by forces invisible to the statistical model but obvious to experts familiar with the case. Subject experts, on the other hand, can become too focused on minutia and miss larger (if more subtle) trends in the data easily recognized by more advanced methodologies. However, the EBMA technique offers a theoretically motivated way to combine the strengths of both methods, while smoothing over their relative weaknesses, to make more accurate predictions.

4. PROPOSED RESEARCH AND TIMELINE

Thus far, we have extended prior research to make EBMA applicable to binary and continuous outcomes in political science. As the above examples demonstrate, the method already increases the accuracy of predictions. However, we propose to expand this research in four ways.

Fully Bayesian estimation: MCMC estimation of EBMA models can more efficiently handle a wider variety of outcome distributions (Vrugt, Diks and Clark 2008). Standard Bayesian methods, such as data augmentation, will allow us to build a set of statistical results and computer algorithms appropriate for an array of assumed outcome distributions. Specifically, we plan to conduct basic research to develop a class of models and MCMC samplers to handle continuos, censored-continuous, binary, and event count data.[15]

[14]The baseline model here is prediction that all votes will be to reverse the lower court. This baseline model is correct for roughly 70% of the votes in the out-of-sample period.

[15]Moreover, as the number of parameters is relatively moderate, Bayesian algorithms also promise to provide fast results while eliminating concerns about false convergence to local maxima that can occur when using EM methods.

Alternative model weights: Currently, EBMA estimates model weights based exclusively on the point predictions of component forecasts. Even for continuous data (e.g., the presidential vote forecasts), the current procedure assumes that the within-forecast variance (σ^2) is constant across models. In other words, model weights do not reflect the uncertainty associated with each model's predictions. Applying both Bayesian and bootstrap methods, we intend to incorporate the entire predictive PDFs of component forecasts so that model weights reflect not only components' accuracy, but also their precision. Poorly calibrated models should be penalized and receive less posterior weight.

A related issue is that, as currently constructed, EBMA makes no explicit adjustment for model complexity. That is, model weights are based solely on the components goodness-of-fit with no effort to adjust for their generalizability. This can lead to excessive weighting of complex and over-fit models. Since component forecasts may be agent-based models, stochastic simulations, multi-level models, and the like, it is necessary to go beyond merely penalizing for the number of parameters (e.g., AIC). Complexity measures must take into account functional form and other concerns. As part of continued research, we plan to incorporate several proposed methods for penalizing complexity into the EBMA method (c.f., Pitt, Myung and Zhang 2002; Pitt and Myung 2002; Spiegelhalter et al. 2002).

Software: We will develop open-source software that will be publicly available. Specifically, we will produce an R package that implements both the binary outcome version we have already developed and the additional extensions just discussed. Moreover, the package will provide a more flexible interface for users interested in ensemble forecasting outside of the weather prediction community than is currently available.

Our specific goals for the software package include: S4 compliance, computationally efficient internal functions written either in C or Java, handling of multiple outcome distributional assumptions and priors with a small set of user functions, Gaussian copula techniques for handling missing data (Hoff 2007), customizable data visualizations to facilitate EBMA and component model comparisons, exemplar datasets and vignettes based on real-world applications of the method to the social and physical sciences, and built-in convergence diagnostics for all Bayesian methods compatible with the 'coda' and 'boa' packages in R. At the completion of the project, we will submit and article to the *Journal of Statistical Software* explaining both the technical details of the package and providing tutorials explaining its available features.

Dissemination of findings: Beyond providing the software and its attendant documentation, we will disseminate the results of our research in three ways. First, we will submit articles explaining the mathematical and technical details of EBMA to journals in political methodology, economics, and applied statistics. Second, we plan to develop and publish at least two extended applications of the method to topics in political science. Our particular focus here will be: (1) improved forecasting of international crisis events; (2) election forecasting with the aim of collaborating with other scholars to generate ensemble predictions for the 2012 U.S. elections. Third, we will offer a workshop on forecasting political outcomes during the first day of the 2012 meeting of the Political Methods Conference (already scheduled to be hosted by the UNC and Duke).

Project Workplan:

01/2012 – 06/2012: In this stage, we will conduct basic research into MCMC estimation of EBMA and prior structures that penalize model complexity and ensure that posterior estimates reflect uncertainty in component forecasts.

07/2012 – 06/2013: In this stage, we will develop, test, and document the software. This will also involve gathering exemplar forecasting datasets for inclusion in package vignettes. These examples will be the basis for subsequent applied research and publication.
07/2013 – 12/2013: This stage will focus on: (1) preparing software and documentation for public dissemination, improving user interfaces, and increasing the computational efficiency of internal functions, and (2) revision and submission of results for publication.

5. Results from Prior NSF Support

5.1. **NSF Grants Received by Michael D. Ward During Previous 5 Years.**

(1) 0827016 ($749,970; PI's sub $150,000) AOC: The Dynamics of Secessionist Regions: Eurasian Unrecognized Quasi-States after Kosovo's Independence 10/01/2008–09/30/2011
(2) 0631531 ($400,000) Longitudinal Network Modeling of International Relations Data 11/15/2006–10/31/2009
(3) 0433927 ($650,000; PI's sub $150,000) The Dynamics of Civil War Outcomes: Bosnia and the North Caucasus 10/01/2004–09/30/2008
(4) 0417559 ($150,000) Network Modeling of International Peace and Trade Data 10/01/2004–09/30/2006

Only one of these grants is still open (# 1), but these funds have only recently (Spring 2011) been transferred to Duke University. The most relevant grant is # 2, which is discussed below.

Summary of Findings: One of our primary findings is that standard hazard regression methods for longitudinal relational data, using variants of proportional hazards models, are unable to properly account for temporal or relational dependence in IR data. We have explored several approaches to modeling the longitudinal dependencies. One models temporal correlations directly as a network. A second uses the temporal evolution of the latent network as a means of imparting dynamic structure into the estimation of the network parameters. A final approach, which we are completing now, involves modeling a separate time-series regression for each pair of countries, but using a special array-variate hierarchical model to allow for similarity in trade patterns across groups of countries. We show that the regularized estimates from this hierarchical model outperform existing methods in out-of-sample prediction of longitudinal trade data.

Broader Impacts: We have presented the research at a number of conferences and in-departmental seminars in the fields of statistics, biostatistics, political science, and geography. We have created the first installment of a series of open-source software packages for the analysis of relational data. These packages are widely used in the social science community conducting network analyses. Finally, we constructed a database of trade and conflict that can be accessed by our software.

Within the first year we completed the following: (1) trained a graduate student in the analysis of longitudinal relational data; (2) constructed and analyzed databases on longitudinal international relations data (including data on conflicts, trade, currency exchange, membership in IGOs); (3) developed new statistical methodologies for multivariate and longitudinal data; (4) conducted basic research in the area of multivariate statistical models, including methods related to copula modeling and reduced-rank matrix models; (5) conducted basic research into the analysis of array data, such as longitudinal trade data, using random-effects versions of multiway array methods such as PARAFAC, and developed an extension of the multivariate and matrix-variate normal distribution appropriate for modeling multiway array data.

Finally, two students learned how to gather and organize data, write technical documents, and perform independent research. Both students completed their Ph.D. in the summer of 2010. One student (John Ahlquist) received two national awards for his dissertation.

Publications Resulting from Award:

- Ward, Michael D., Randolph M. Siverson, and Xun Cao. 2007. “Disputes, Democracies, and Dependencies: A Re-examination of the Kantian Peace”. *American Journal of Political Science* 51(3):583-601.
- Ward, Michael D. and Peter D. Hoff. 2008. Analyzing Dependencies in Geo-Politics and Geo-Economics. In *Contributions to Conflict Management, Peace Economics, and Development, Volume 6, War, Peace and Security*, ed. Jacques Fontanel and Manas Chatterji. Bingley, UK: Emerald Publishing, pp. 133-160.
- Krivitsky, Pavel, Mark Handcock, Adrian Raftery and Peter Hoff. 2009. “Representing Degree Distributions, Homophily and Clustering in Social Networks with Latent Cluster Models”. *Social Networks* 31(3):204-213.
- Hoff, Peter. 2008. “Modeling Homophily and Stochastic Equivalence in Symmetric Relational Data”. *Advances in Neural Information Processing Systems* 20: 667-674.
- Hoff, Peter. 2009. “Simulation of the Matrix Bingham-von-Mises-Fisher Distribution, With Applications to Multivariate and Relational Data”. *Journal of Computational and Graphical Statistics* 18(2):438–456.
- Hoff, Peter. 2009. “A hierarchical eigenmodel for pooled covariance estimation”. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 71(5):971–992.
- Ward, Michael D. 2010. Statistical Analysis of International Interdependencies. In *The International Studies Encyclopedic Compendium: Scientific Studies of International Processes, Volume 10*, ed. Paul F. Diehl and James D. Morrow, pp. 6615-6628.
- Bakke, Kristin M., Xun Cao, John O’Loughlin and Michael D. Ward. 2009. “Social Distance in Bosnia and the North Caucasus Region of Russia: Inter- and intra-ethnic attitudes and identities”. *Nations and Nationalism* 15(2):227-253.
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- Ahlquist, John S. 2008. “Building and Using Strategic Capacity: Labor Union Confederations and Economic Policy”. Thesis. Published. Bibliography: Doctoral Dissertation, University of Washington.
- Raftery, Adrian E. and Michael D. Ward. 2010. *Statistical Methodology: Special Issue on Statistical Methods for the Social Sciences*. Elsevier. Volume 8.

5.2. **NSF Grants Received by Jacob M. Montgomery.**

(1) SES-1023762 ($12,000) Doctoral Dissertation Research in Political Science: The Causes, Consequences, and Measurement of Perceived Political Control, 09/2010-08/2011.

Summary of Findings: I developed, evaluated, and validated a measure of perceived political control. I show that the scale is distinct from extant measures, and has superior explanatory power for predicting important behaviors in the future. In work currently underway, I show that actively supporting a winning candidate plays a causal role in shaping these control beliefs.

*Broader Impacts:*I have presented the research at a conference. In addition, I developed an online platform for applying computer-based psychological testing techniques for more efficient administration of large scale in online surveys to be released for public use.

Publications:

- Jacob M. Montgomery, “An Evolutionary Theory of Democracy: Dynamic Evolutionary Models of American Party Competition with an Empirical Application to the Case of Abortion Policy from 1972-2010”, Doctoral Dissertation, Duke University, Sept (2011).

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Whiteley, Paul F. 2005. "Forecasting Seats from Votes in British General Elections." *The British Journal of Politics & International Relations* 7(2):165–173.

MICHAEL D. WARD

Professional Preparation.

B.A. (Honors), Indiana University, 1970.
Ph. D., Political Science, Northwestern University, 1977.
Gordon Scott Fulcher Post Doctoral Research Associate & Visiting Assistant Professor, Department of Political Science, Northwestern University, 1977-1980.

Appointments.

Professor of Political Science, Duke University, 2009–present.
Professor of Political Science, University of Washington, 1997–2009.
Chaire Municipale & Professeur, Faculté des Sciences Économiques, Université Pierre Mendès France, Grenoble, France, 2000-2005.
Professeur Invitée et Emerité, Faculté des Sciences Économiques, Université Pierre Mendès France, Grenoble, France, 1990-1991.
Professor of Political Science, University of Colorado, 1982-1998.
Research Scientist, Wissenschaftszentrum Berlin, International Institute for Comparative Social Research, 1980-1982.
Gordon Scott Fulcher Post Doctoral Research Associate & Visiting Assistant Professor, Department of Political Science, Northwestern University, 1977-1980.

Publications.

Related to Proposed Activities.

1 Weidmann, Nils B. and Michael D. Ward. 2010. "Predicting Conflict in Space and Time". *Journal of Conflict Resolution* 54(6): 883-910.
2 Ward, Michael D., Brian D. Greenhill and Kristin M. Bakke. 2010. "The Perils of Policy by P-Value: Predicting Civil Conflicts". *Journal of Peace Research* 48(4):3673-375. (Winner of best article in journal during 2010).
3 Ward, Michael D. and Kristian Skrede Gleditsch. 2008. *Spatial Regression Models*. Thousand Oaks, California and London: Sage Publishers
4 Greenhill, Brian D., Michael D. Ward and Audrey Sacks. 2011. "The Separation Plot: A New Visual Method for Evaluating the Predictive Power of Binary Models". *American Journal of Political Science* in press.
5 Ward, Michael D. and Kristian Skrede Gleditsch. 2002. "Location, Location, Location: An MCMC Approach to Modeling the Spatial Context of War and Peace". *Political Analysis* 10(3):244–260.

Five Other Significant Publications.

1 Ward, Michael D., Randolph M. Siverson and Xun Cao. 2007. "Disputes, Democracies, and Dependencies: A Re-examination of the Kantian Peace". *American Journal of Political Science* 51(3):583-601
2 Ward, Michael D. and Kristian Skrede Gleditsch. 1998. "Democratizing for Peace". *American Political Science Review* 92(1):51–61
3 Ward, Michael D. and David R Davis. 1992. "Sizing up the Peace Dividend: Economic Growth and Military Spending in the United States, 1948–1996". *American Political Science Review* 86(3):748–758.

4 Mintz, Alex and Michael D. Ward. 1989. "The Political Economy of Military Spending in Israel". *American Political Science Review* 83(2):521–533.

5 Ward, Michael D. 1984. "Differential Paths to Parity: A Study of the Contemporary Arms Race". *American Political Science Review* 78(2):297–317.

Synergistic Activities. While on the executive council of the Center for Statistics and the Social Sciences, I helped to develop a university wide curriculum in applied statistical methods that would be available to social science departments across the university. We also created new fields of applied statistics within a total of five departments; our first was in the department of Political Science. These served to broaden and deepen training in statistical methods for social science graduate students at the University of Washington.

I have also organized several conferences aimed at helping scholars in the social sciences to apply new approaches to the study of social phenomenon. One of these was a conference at the University of Washington on Spatial and Network approaches to studying political phenomenon, which was sponsored in part by the Center for Statistics and the Social Sciences, but also funded in part by a grant from the Center for Spatially Informed Social Sciences.

In 2010, I also organized and was the local host for the 2010 Duke Conference on Networks in Political Science, an international and multidisciplinary gathering of about 200 scholars and practitioners of network science.

Collaborators.

Collaborators and co-Editors in the past 48 months. John Ahlquist, Kristin Bakke, Xun Cao, Kristin Gleditsch, Brian Greenhill, Peter Hoff, Aseem Prakash, Ian Lustic, Nils Metternich, Clionadh Raleigh, Adrian Raftery, Phil Schrodt, Stephen Shellman, Randolph Siverson, Katherine Stovall, & Nils Weidmann.

Graduate Advisors and Postdoctoral Sponsors.

My advisors: James A. Caporaso (University of Washington), Harold Guetzkow (RIP), Karl W. Deutsch (RIP)

My advisees: John Ahlquist (University of Wisconsin), Xun Cao (Penn State University), Brian Greenhill (Dartmouth University), Nils Weidmann (Yale University), Umut Aydin (Boğaziçi University), Christian Breunig (University of Toronto), Kristian Gleditsch (Essex University), David Brown (University of Colorado), Michael Shin (UCLA)

JACOB M. MONTGOMERY

Professional Preparation.

B.A. (*Summa Cum Laude*), Wake Forest University, 2002.
M.S., Statistical Science, Duke University, 2009.
Ph. D., Political Science, Duke University, 2011.

Appointments.

Assistant Professor of Political Science, Washington University in St. Louis, 2011–present.

Publications.

Related to Proposed Activities.

1 Montgomery, Jacob M. and Brendan Nyhan. 2010. "Bayesian Model Averaging: Theoretical Developments and Practical Applications". *Political Analysis* 18(2): 245-270.

2 Montgomery, Jacob M., Alexandra Cooper, Jerome Reiter and Shuo Guan. 2008. "Non-Response Bias on Dimensions of Political Activity Amongst Political Elites". *International Journal of Public Opinion Research* 20(4): 223-231.

Other Significant Publications.

1 Aldrich, John H., Jacob M. Montgomery and Wendy Wood. Forthcoming. "Turnout as a Habit".*Political Behavior*. `http://www.springerlink.com/content/45501465ux177435/`

2 Montgomery, Jacob M., Kristie Long Foley and Mark Wolfson. 2006. "Enforcing the Minimum Drinking Age: State, Local, and Agency Characteristics Associated With Compliance Checks and Cops in Shops Programs". *Addiction* 101(2): 223-231.

Synergistic Activities. From 2008-2010, I helped found and organize a weekly methods workshop involving faculty and graduate students at both Duke University and the University of North Carolina.

Collaborators.

Collaborators and co-Editors in the past 48 months. John H. Aldrich (Duke), Alexandra Cooper (Duke), Christophe DeSante (Duke), Melanie Freeze (Duke), Shuo Guan, David Neal (University of Southern California – Psychology), Brendan Nyhan (Dartmouth), Jerome Reiter (Duke – Statistical Science), David Sparks (Duke), Wendy Wood (University of Southern California – Psychology).

Graduate Advisors and Postdoctoral Sponsors.

Ph.D. Dissertation Advisors: John H. Aldrich (Duke), Nancy Burns (University of Michigan), Michael C. Munger (Duke), David Rohde (Duke)
M.S. Thesis Advisors: Jerome Reiter (Duke – Statistical Science), David Dunson (Duke – Statistical Science)

Data Management Plan

Data and programs from this research will be deposited in a Dataverse archive at `thedata.org` within 12 months of the end of the project.

Budget Justification (DUKE)

The PI, Michael Ward, is budgeted for 0.5 months in each year. The faculty benefit rate for Ward is XX%.

The PIs ask for %XX,XXX to cover the cost of a graduate assistant at Duke University budgeted to work at 50% effort for one year (June, 2012 - May, 2013). The graduate student benefit rate is XX.X%. The combined cost for graduate student assistance will be $XX,XXX.

The PIs ask for $2,500 for travel. This money is expected to cover 1 trip for in-person collaborative research in St. Louis, MO. In addition, the PI and one graduate student will attend the yearly Political Methodology Conference.

Finally, Duke University's current indirect cost rate with DHHS is 6X.X%.

Budget Justification (Washington University in St. Louis)

The CO-PI, Jacob M. Montgomery, is budgeted for 1 months in each year. The faculty benefit rate for Montgomery is XX%. The combined cost will be $25,000.

The PIs ask for %XX,XXX to cover the cost of a graduate assistant at Washington University in St. Louis budgeted to work at 50% effort for one year (June, 2012 - May, 2013). The graduate student benefit rate is XX.X%. The combined cost for graduate student assistance will be $XX,XXX.

The PIs ask for $2,500 for travel. This money is expected to cover 2 trips for in-person collaborative research in Durham, NC. In addition, Montgomery will attend the yearly Political Methodology Conference.

Finally, Washington University's current indirect cost rate with DHHS is 5X.X%.

TODO

(1) Florian to CAREFULLY review references to ensure that they include: article title, journal title, volume number, page numbers, authors, and year of publication. Pay special attention to everything with a URL to make sure we are citing it the same across. This also includes all citations in the Ward/Montgomery biographies and in section 5 of the proposal.
(2) Budget (one for each school)
(3) Fill in numbers on Budget justification (One for each school)
(4) Facilities, Equipment and Other Resources (one for each school)
(5) Make all of this conform to the "collaborative proposals" guidelines reproduced belo.
(6) Get the Fastlane "cover sheet" filled out correctly (and identically in both locations).

4. Collaborative Proposals (pg. II-23

A collaborative proposal is one in which investigators from two or more organizations wish to collaborate on a unified research project. Collaborative proposals may be submitted to NSF in one of two methods: as a single proposal, in which a single award is being requested (with subawards administered by the lead organization); or by simultaneous submission of proposals from different organizations, with each organization requesting a separate award. In either case, the lead organizations proposal must contain all of the requisite sections as a single package to be provided to reviewers (that will happen automatically when procedures below are followed). All collaborative proposals must clearly describe the roles to be played by the other organizations, specify the managerial arrangements, and explain the advantages of the multi-organizational effort within the Project Description. PIs are strongly encouraged to contact the cognizant NSF Program Officer prior to submission of a collaborative proposal.

b. Submission of a collaborative proposal from multiple organizations

In many instances, simultaneous submission of proposals that contain the same Project Description from each organization might be appropriate. For these proposals, the project title must begin with the words "Collaborative Research:". The lead organization's submission will include a Cover Sheet, Project Summary, Project Description, References Cited, Biographical Sketches, Budgets and Budget Justification, Current and Pending support, and Facilities, Equipment and Other Resources for their organization. If applicable, the lead organizations submission also must include a supplemental mentoring plan that must not exceed one page, and that addresses the mentoring activities to be provided for all postdoctoral researchers supported under the entire collaborative project. See GPG Chapter II.C.2.j for additional guidance on mentoring and data management plan requirements for collaborative proposals. Non-lead organization submissions will include all of the above for their organization except the project summary, project description, and references cited which are the same for all collaborating organizations. FastLane will combine the proposal submission for printing or electronic viewing.

To submit the collaborative proposal, the following process must be completed:

(i) Each non-lead organization must assign their proposal a proposal PIN. This proposal PIN and the temporary proposal ID generated by FastLane when the non-lead proposal is created must be provided to the lead organization before the lead organization submits its proposal to NSF.

(ii) The lead organization must then enter each non-lead organization(s) proposal PIN and temporary proposal ID into the FastLane lead proposal by using the "Link Collaborative Proposals" option found on the FastLane "Form Preparation" screen. Given that such separately submitted proposals constitute a single proposal submission to NSF, it is imperative that the proposals be submitted within a reasonable timeframe to one another.

(iii) All components of the collaborative proposal must meet any established deadline, and, failure to do so may result in the entire collaborative proposal being returned without review.