Structural Change in U.S. Presidents' Use of Force

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Has there been a structural change in the way U.S. presidents use force abroad since the nineteenth century? In this article, I investigate historical changes in the use of force by U.S. presidents using Bayesian changepoint analysis. In doing so, I present an integrated Bayesian approach for analyzing changepoint problems in a Poisson regression model. To find the nature of the breaks, I estimate parameters of the Poisson regression changepoint model using Chib's (1998) hidden Markov model algorithm and Frühwirth-Schnatter and Wagner's (2006) data augmentation method. Then, I utilize transdimensional Markov chain Monte Carlo methods to detect the number of breaks. Analyzing yearly use of force data from 1890 to 1995, I find that, controlling for the effects of the Great Depression and the two world wars, the relationship between domestic conditions and the frequency of the use of force abroad fundamentally shifted in the 1940s.

Scholars of international politics have long debated whether and how domestic politics affect a U.S. president's decision to use force abroad (Fordham 1998a, 1998b, 2002; Gowa 1998; Howell and Pevehouse 2005, 2007; James and Oneal 1991; Meernik and Waterman 1996; Mueller 1970; Ostrom and Job 1986; Smith 1996). The most controversial claim in this literature is the diversionary hypothesis: incumbent presidents use force abroad to divert public attention away from unfavorable domestic circumstances.

Figure 1 shows the annual changes in the use of force between 1870 and 1995. Reflecting substantial shifts in international relations and U.S. politics, the frequency of the use of force has gone through several significant changes since the late nineteenth century. Given these dramatic shifts, any theoretical hypothesis about the use of force that assumes a static intertemporal causal process rests on shaky ground.

In fact, historical changes in the use of force have been at the center of the debate in the literature. For example, Gowa (1998) argues that previous findings in support of the diversionary hypothesis are contingent upon the fact that these studies often only cover the period after the 1940s or the 1960s. When Gowa extends the time frame back to 1870 using the Militarized Interstate Disputes data, she finds "the use of force abroad is invariant to both the domestic political calendar and the partisan composition of government" (1998, 307). However, Fordham questions Gowa's conclusion, arguing that because Gowa "does not consider whether U.S. decision makers were more responsive to economic conditions or other independent variables in different historical periods . . . historical change in the modeled relationships could threaten the validity of her results" (2002, 574–75).[1]

The importance of checking theoretical models for sensitivity to historical contingencies is hardly confined

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[1]Due to the lack of proper empirical tools, most researchers resort to the dummy variable approach to check the time-constancy of regression parameters. There are several issues that make the application of dummy variables to changepoint problems troublesome. First and foremost, defining a dummy variable to capture the effects of structural changes requires strong prior knowledge about the location, the number, and the duration of structural changes. This kind of information is not available to researchers in most cases. Second, it is very difficult to specify a time dummy variable since we do not have clear knowledge about the effects of structural changes on other covariates a priori. Lastly, the dummy variable approach is less desirable for making statistical inferences about a changepoint problem because it cannot provide a probabilistic estimate of regime changes. For example, most scholars of international relations agree that the Cold War had a significant effect on U.S. presidents' use of force. However, specifying a dummy variable indicating the Cold War period in a regression model requires strong knowledge about (1) when the *effect* of the Cold War started, (2) whether other events such as the Korean War or the Vietnam War during the Cold War had separate effects from the Cold War, and (3) whether the Cold War had multiplicative effects with other covariates on the use of force.

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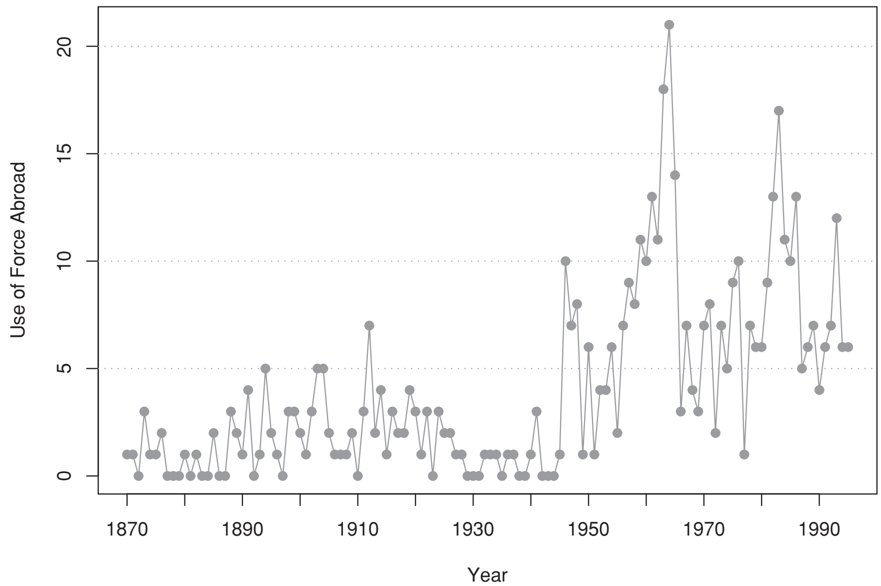
FIGURE 1 U.S. Presidents' Use of Force Abroad from 1870 to 1995



Source: The unit of measure is the frequency of force by a U.S. president in a given year (Fordham and Sarver 2001).

to the study of the use of force. In fact, Lieberman (2002) and Büthe (2002) argue that most empirical models in political science are based on the assumption of stable causal processes and are consequently not suitable for capturing dynamic changes in theoretical relationships.[2]

In this article, I introduce a Bayesian changepoint model for an event-count model that investigates historical changes in the use of force by U.S. presidents. Based on Chib's (1998) multiple changepoint model, I develop a Poisson regression changepoint model by utilizing Frühwirth-Schnatter and Wagner's (2006) data augmentation method. I also develop a new model selection method for the Poisson regression changepoint model via transdimensional Markov chain Monte Carlo methods. I discuss how to use the results of changepoint analysis to make inferences about the causes of structural changes.

The Bayesian changepoint analysis demonstrates that there was a structural break in the way U.S. presidents used force abroad in the 1940s after controlling for domestic political factors and the immediate effects of the Great Depression and two world wars. The effect of divided party control of government on the use of force disappears after the break. The positive effect of high unemployment, which has been suggested as important evidence for the diversionary hypothesis in previous literature (Fordham 1998a, 1998b, 2002; Howell and Pevehouse 2005), is found to exist only after the structural break. Also, the changepoint analysis finds that the effect of partisan support for presidents in the Senate (House) becomes significant and positive (negative) after the break. Most strikingly, these regime-dependent effects of domestic political economic factors disappear when we ignore the breaks in the data-generating process as we typically do in the regression analysis with constant parameters.

Although this article focuses on the changepoint model for count data, the implications of the article highlight the general advantage of Bayesian changepoint models in testing theoretical models of structural changes and in discovering previously unknown historically contingent theoretical relationships.

Bayesian Changepoint Analysis

A changepoint problem arises whenever researchers find the time-constancy of the causal relationship in their model to be suspect. In the context of regression models, a changepoint problem occurs whenever "parameters of a model change a small number of times in response to forces within or outside the model" (Poirier 1976, 1). In the context of the use of force example, the question of

[2]Some notable exceptions, hardly exhaustive, include Beck (1983), McGinnis and Williams (1989), Freeman et al. (1998), Freeman, Hays, and Stix (2000), Brandt et al. (2000), Martin and Quinn (2002), Brandt and Freeman (2006), and Spirling (2007).

the effects of domestic conditions on the frequency of the use of force by U.S. presidents turns into a changepoint problem if there is a substantive reason to question the time-constancy of presidential decision rules on the use of force during the time period under consideration.

Various techniques have been developed to detect and estimate unknown changepoints in classical statistics (Andrews 1993; Andrews and Ploberger 1994; Bai and Perron 1998; Brown, Durbin, and Evans 1975; Chow 1960; Hamilton 1989; Nyblom 1989; Quandt 1958) and in Bayesian statistics (Barry and Hartigan 1993; Carlin, Gelfand, and Smith 1992; Chernoff and Zacks 1964; Chib 1996, 1998; Green 1995). From these methods, I chose Chib's (1998) Bayesian approach because of its flexibility in dealing with limited dependent variables and its computational advantage in handling high-dimensional parameter vectors and multiple changepoints.

The key to Chib's innovation in changepoint models is the reparameterization of a changepoint model as a special type of finite mixture models through the introduction of latent state variables ($\mathbf{s}$) that take discrete values from 1 to the total number of hidden regimes (M).

$$\mathbf{s} = \{(s_1, \ldots, s_T) : s_t \in \{1, \ldots M\}, t = 1, \ldots, T\}$$

Each discrete value indicates the type of data-generating regime at each time unit (t). We can find substantive meanings of the latent states in many applications. For example, the latent states in the use of force example may indicate historical periods characterized by distinctive decision rules employed by U.S. presidents in deploying forces abroad. We only observe the outcomes of the changed decision rules, in the form of the frequency of the use of force, but we never observe the changes in the decision rules themselves. Note that the information conveyed by the latent state variables is equivalent to break-points as changes in the latent state variable denote break-points.

In Chib's model, the transition of hidden states is constrained to move forward. This nonergodic Markov chain provides many advantages in modeling and estimating structural breaks. First, due to the constraint that makes the regime changes irreversible, we can easily obtain the initial probability: the initial probabilities of all other states except regime 1 are zero. Second, we do not need to impose arbitrary constraints on regression parameters to avoid the label-switching problem. Researchers do not need to restrict the directions of parameter changes in the forthcoming regimes. Last, changepoint models can identify regime-switching movements by treating recurring regimes as new ones. Suppose a decision-making rule was used in one decade, ignored in the next, and then brought back into use in a third decade. Then, changepoint models will identify three distinct regimes from the model and data to researchers. Researchers can test whether the first regime and the third regime are identical using the outcomes of changepoint models.[3]

Based on the latent state framework, the Poisson regression changepoint model is defined by letting parameters of the Poisson regression model follow a Markov regime transition. Let y_t be an event count at t, m be a hidden state (or regime) at t, and $\boldsymbol{\beta}_m$ be the regression parameter vector corresponding to the state m. If we choose multivariate normal priors for regression parameters and the Beta prior for first-order transition probabilities, or the Dirichlet prior in the case of higher-order Markov processes, a fully Bayesian form of the Poisson regression changepoint model augmented by latent state variables can be written as follows.

$$\begin{aligned} p(\boldsymbol{\beta}, \mathbf{P}, \mathbf{s}|\mathbf{y}) &\propto \prod_{t=1}^{T} p(y_t|\boldsymbol{\beta}, \mathbf{P}, \mathbf{s}) \prod_{i=1}^{M} p(\boldsymbol{\beta}_i)\, p(\mathbf{p}_i) \\ &= \mathcal{P}oisson(y_1|\boldsymbol{\beta}_1) \\ &\quad \times \prod_{t=2}^{T} \left\{ \sum_{m=1}^{M} \mathcal{P}oisson(y_t|\boldsymbol{\beta}_m) \Pr(s_t = m|\boldsymbol{\beta}, \mathbf{P}) \right\} \\ &\quad \times \prod_{i=1}^{M} \mathcal{N}(\boldsymbol{\beta}_{0,i}, \mathbf{B}_{0,i}) \mathcal{B}eta(a_i, b_i) \end{aligned}$$

where $\mathbf{p}_i$ is a vector consisting of nonzero elements in the ith row in $\mathbf{P}$, and $\boldsymbol{\beta}_{0,i}$, $\mathbf{B}_{0,i}$, a_i, b_i are regime-specific hyperparameters that need to be chosen by researchers.

Generally speaking, the estimation of a multiple changepoint model consists of three steps. First, hidden state variables are sampled from $p(\mathbf{s}|\mathbf{y}, \boldsymbol{\beta}, \mathbf{P})$ using Chib's (1998) recursive algorithm. Second, given the sampled state variables, transition probabilities are drawn from binomial distributions: $p(\mathbf{P}|\mathbf{y}, \boldsymbol{\beta}, \mathbf{s})$. The last step in the simulation is the sampling of model-specific parameters given the sampled state variables and transition probabilities: $p(\boldsymbol{\beta}|\mathbf{y}, \mathbf{s}, \mathbf{P})$. In the following section, I will explain one efficient way to perform the last step in the estimation process of the Poisson regression changepoint model.

[3] If we define $p_{ij} = \Pr(s_t = j|s_{t-1} = i)$ as the probability of moving to state j from state i at time t, the time homogeneous, nonergodic first-order Markov transition matrix can be written as follows:

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} & 0 & \ldots & 0 \\ 0 & p_{22} & p_{23} & \ldots & 0 \\ & & \ldots\ldots\ldots\ldots & & \\ 0 & 0 & 0 & p_{M-1,M-1} & p_{M-1,M} \\ 0 & 0 & & 0 & 1 \end{pmatrix}$$

Data Augmentation Using Hidden Interarrival Times

It is well known in Bayesian literature that when we add covariates to a Poisson model, conditional distributions do not take known distributional forms. Consequently, the estimation of a Poisson regression model requires computationally expensive simulation techniques such as Metropolis-Hastings (MH) algorithms.[4] One way to reduce the computational cost in a discrete data context is to transform the model into the linear Gaussian model by augmenting latent variables. Frühwirth-Schnatter and Wagner (2006) proposed a data augmentation method for count data using an auxiliary mixture sampling method originally developed by Kim, Shephard, and Chib (1998).

Frühwirth-Schnatter and Wagner take advantage of the basic assumption in the Poisson process that the time between successive events, called interarrival times, is independent and follows an exponential distribution. Taking the logarithm of interarrival times transforms a Poisson regression model into a linear regression model with a log Exponential (1) error distribution.[5] Then, we can link the length of the time between the $j-1$th event and the jth event within time interval t, τ_{tj}, with exogenous covariates ($\mathbf{x}_t$) through observed counts (y_t) as follows:

$$p(y_t|\lambda_t) = \frac{e^{-\lambda_t}\lambda_t^{y_t}}{y_t!}$$

$$\tau_{tj} \sim \mathcal{E}xp(\lambda_t) = \frac{\mathcal{E}xp(1)}{\lambda_t}$$

$$\log \tau_{tj} = \mathbf{x}_t'\boldsymbol{\beta}_m + \varepsilon_{tj}, \quad \varepsilon_{tj} \sim \log(\mathcal{E}xp(1))$$

where $\mathcal{E}xp(\cdot)$ is an Exponential distribution and $\boldsymbol{\beta}_m$ is the regression parameter vector corresponding to the hidden state m at time t.

To complete the transformation to the linear Gaussian model, the log Exponential (1) error distribution is approximated by a mixture of five Gaussian distributions following the idea of Kim, Shephard, and Chib (1998).

$$p(\varepsilon_{tj}) = \exp(\varepsilon_{tj} - \exp(\varepsilon_{tj})) \approx \sum_{r=1}^{5} w_r\, f_N(m_r, s_r^2)$$

where f_N is a Gaussian density function, w_r is the weight of each Gaussian density, and m_r and s_r^2 are two moments of corresponding Gaussian densities.

Model Selection Using Transdimensional MCMC Methods

Since researchers do not know the "true" number of changepoints *ex ante*, detecting the number of changepoints using model selection methods is critical in changepoint analysis. Note that changepoint model comparison cannot be done with usual model comparison tools such as likelihood ratios or Akaike Information Criterion because of the nonnested nature of changepoint models. However, nonnestedness does not cause a problem in Bayesian model comparison.[6]

In principle, the goal of Bayesian model selection is to assess posterior probability of the model. There are two approaches in assessing posterior model probability in Bayesian statistics. One is to compute the ratio of marginal likelihoods of competing models. Each marginal likelihood yields the probability of observing the data given the model under consideration. A ratio of marginal likelihoods known as the Bayes factor provides "a summary of the evidence provided by the data in favor of one

[4] The Gibbs sampler draws samples of the target distribution sequentially from conditional distributions, which take known distributional forms (Geman and Geman 1984). In contrast, when conditional distributions do not take known distributional forms, we should employ Metropolis-Hastings type algorithms that involve generating a proposal value and computing a probability of a move at each simulation step.

[5] However, this transformation of the Poisson process using hidden interarrival times in changepoint analysis comes with cost: the transformed duration model assumes that regression parameters are constrained to be constant within a Poisson time interval (t). Thus, as one anonymous reviewer points out, possible parameter changes during a Poisson time interval cannot be addressed in this framework. This problem is caused by the unobservable interarrival times and hence exogenous variables cannot be lined up with hidden interarrival times in an explicit manner. However, the time interval in the Poisson process is arbitrary. Thus, one way to relieve the strict assumption of constant parameters during the time interval is to choose a shorter Poisson time unit. As we shorten the time intervals, the assumption of constant parameters within each one becomes less problematic.

[6] Let α and β denote linear Gaussian parameters for a one-changepoint model and a two-changepoint model, respectively. α_{ij} denotes the jth parameter of the one-changepoint model in state i and β_{ij} is defined in the same way for the two-changepoint model. y_i denotes outcome variables corresponding to state i, and x_i is an exogenous variable corresponding to state i in each model. These two models can be written with constant variances as follows.

$$\begin{aligned} y_1 &= \alpha_{11} + \alpha_{12}x_1 + \varepsilon_1, \quad \varepsilon_1 \sim \mathcal{N}(0, \sigma_1^2) \\ y_2 &= \alpha_{21} + \alpha_{22}x_2 + \varepsilon_2, \quad \varepsilon_2 \sim \mathcal{N}(0, \sigma_1^2) \end{aligned} \tag{1}$$

$$\begin{aligned} y_1 &= \beta_{11} + \beta_{12}x_1 + \epsilon_1, \quad \epsilon_1 \sim \mathcal{N}(0, \sigma_2^2) \\ y_2 &= \beta_{21} + \beta_{22}x_2 + \epsilon_2, \quad \epsilon_2 \sim \mathcal{N}(0, \sigma_2^2) \\ y_3 &= \beta_{31} + \beta_{32}x_3 + \epsilon_3, \quad \epsilon_3 \sim \mathcal{N}(0, \sigma_2^2) \end{aligned} \tag{2}$$

It is obvious that the parameters of the one-changepoint model in equation (1) cannot be reduced to the parameters of the two-changepoint model in equation (2) by a set of linear restrictions. See Pesaran and Weeks (2001) and Clarke (2001) for the nonnested model comparison. The nonnested model comparison using Bayesian methods is discussed in general by Carlin and Louis (2000) and in the context of finite mixture models by Frühwirth-Schnatter (2006).

scientific theory, represented by a statistical model, as opposed to another" (Kass and Raftery 1995, 777).[7] Algorithms to quantify approximate marginal likelihoods are available for a wide range of models (Chib 1995; Chib and Jeliazkov 2001; Meng and Wong 1996).

Alternatively, one can quantify posterior model probabilities of competing models using transdimensional MCMC methods (Carlin and Chib 1995; Green 1995). Unlike standard MCMC methods, which work under one (local) model, transdimensional MCMC methods are designed to visit different models (with different parameters).[8]

Let $\mathbf{y}$ be data and $\boldsymbol{\theta}_k$ be a parameter vector pertaining to model k. While the target of inference in standard MCMC methods is the posterior distribution of parameters, $p(\boldsymbol{\theta}_k|k, \mathbf{y})$, transdimensional MCMC methods are designed to sample from the *joint posterior distribution of the model index and model-specific parameters*, which is the product of posterior model probabilities, $p(k|\mathbf{y})$, and posterior distributions of model-specific parameters: $p(\boldsymbol{\theta}_k|k, \mathbf{y})$.

$$p(\boldsymbol{\theta}_k, k|\mathbf{y}) = p(k|\mathbf{y})\, p(\boldsymbol{\theta}_k|k, \mathbf{y})$$

In order to build a Markov chain that jointly samples k and $\boldsymbol{\theta}_k$, we need to design (1) a model space proposal, which determines how to jump over the model space, (2) model-specific parameter proposals, which concerns how to construct model-specific parameters when a new model is chosen, and (3) the formula to compute the acceptance probability of the proposed move. In the following paragraphs, I introduce a transdimensional MCMC method for the Poisson regression changepoint model.

First, following Godsill (2001), I generate a model proposal from a discretized Laplacian density with $\lambda = 0.4$. The discretized Laplacian density is symmetric and hence model proposal densities are canceled out in the computation of the acceptance rate.

$$J(k \to k') \propto \exp(-\lambda|k' - k|), \quad k \in 0, \ldots, k_{\max}$$

Second, I choose an independent Metropolis-Hastings proposal for model-specific parameter proposals to simplify the computation of the acceptance rate (Dellaportas, Forster, and Ntzoufras 2002; Vrontos, Dellaporhas, and Politis 2000).[9] The main disadvantage of an independence sampler is that it is often very difficult to find a proposal density that approximates the target density. However, this difficulty does not cause great concern in the case of the Poisson regression changepoint model, as the initial Gibbs runs are good approximations of the candidate models. I use multivariate Gaussian distributions for the proposal of slope parameters ($\boldsymbol{\beta}$) and the Beta distribution for the proposal of the transition probabilities (p_i). Prior values are obtained from 1,000 initial MCMC runs for each model. These pilot runs provide reasonable inputs for proposals for reversible chains so that reversible chains do not drift too far from local target distributions.

Finally, assuming researchers do not have strong prior knowledge about the degree of plausibility of competing models, I impose the same prior probability on each model.

Using these schemes, the acceptance rate can be simplified as follows.

$$\alpha = \min\left(1, \frac{p(\boldsymbol{\theta}'_k|k', \mathbf{y})q(k, \boldsymbol{\theta}_k)}{p(\boldsymbol{\theta}_k|k, \mathbf{y})q(k', \boldsymbol{\theta}_{k'})}\right)$$

Because the estimation of parameters is a multistep process, I now summarize the algorithm that implements the above-mentioned transdimensional MCMC method

[7] Formally, the Bayes factor is

$$BF_{i|j} = \frac{m(\mathbf{y}|\mathcal{M}_i)}{m(\mathbf{y}|\mathcal{M}_j)}$$

where $BF_{i|j}$ is a Bayes factor comparing model $\mathcal{M}_i$ to model $\mathcal{M}_j$, and $m(\mathbf{y}|\mathcal{M}_i)$ is the marginal likelihood under model $\mathcal{M}_i$ which is defined as

$$m(\mathbf{y}|\mathcal{M}_i) = \int p(D|\boldsymbol{\theta}_i, \mathcal{M}_i)\, p(\boldsymbol{\theta}_i, \mathcal{M}_i)\, d\boldsymbol{\theta}_i$$

where D is observed data.

[8] A brief history of transdimensional MCMC methods would be helpful here. Initially, the method was proposed by Carlin and Chib (1995), utilizing the Gibbs sampling of model parameters and model indices. Green (1995) proposes an alternative method called reversible jump MCMC that switches between adjacent models by matching dimensionality of adjacent models via auxiliary random variables. Besag (1997) and Godsill (2001) show these two competing frameworks are equivalent in the sense that they are all Metropolis-Hastings algorithms in model space. All the transdimensional MCMC methods are distinguished by the type of movement (e.g., the Gibbs sampler, random walk, independent, and accept-reject) and the choice of model proposal density.

[9] A main challenge in applying transdimensional MCMC methods is computing the acceptance rate of model jumps. For example, the following equation shows the acceptance rate in the reversible jump MCMC (RJMCMC) sampler, which is one of most popular transdimensional MCMC methods (Green 1995).

$$\alpha = \min\left(1, \frac{p(\mathbf{y}|\boldsymbol{\theta}_{k'}, k')\, p(\boldsymbol{\theta}_{k'})\, p(k')\, J(k' \to k) q(u', \boldsymbol{\theta}_{k'}, k', k)}{p(\mathbf{y}|\boldsymbol{\theta}_k, k)\, p(\boldsymbol{\theta}_k)\, p(k)\, J(k \to k') q(u, \boldsymbol{\theta}_k, k, k')} \left|\frac{\partial g_{k,k'}(\boldsymbol{\theta}_k, u)}{\partial(\boldsymbol{\theta}_k, u)}\right|\right)$$

where k is a model indicator, $J(k \to k')$ is a proposal from model k to model k', $q(u, \boldsymbol{\theta}_{i=k}, k, k')$ is a proposal density of a full parameter vector from model k to model k', u is an auxiliary vector that matches the dimensionality between models, and $g_{k,k'}$ is a bijection between $(\boldsymbol{\theta}_k, u)$ and $(\boldsymbol{\theta}_{k'}, u')$. If a proposed model is drawn from an independent and symmetric density, then the Jacobian related to parameter transformation equals 1 and cancels out.

for a Poisson regression changepoint model. I define $\boldsymbol{\tau}$ as the (vector of log transformed) interarrival times; η indicates component indicators of five Gaussian mixture distributions for the Gaussian approximation of the log Exponential (1) distribution; $\boldsymbol{\theta}_{k'}$ denotes the proposed parameters, the dimension of which corresponds to model k'. For simple notation, I drop regime-specific subscripts.

Transdimensional MCMC Algorithm for a Poisson Regression Changepoint Model.

1. Propose a new model $\mathcal{M}_{k'}$ with probability $J(k \to k')$.
2. Draw $\boldsymbol{\theta}_{k'}$ from $q(k', \boldsymbol{\theta}_{k'})$.
3. Accept the new model with probability,

$$\alpha = \min\left(1, \frac{p(k', \boldsymbol{\theta}_{i=k'}|\mathbf{y})q(k, \boldsymbol{\theta}_{i=k})}{p(k, \boldsymbol{\theta}_{i=k}|\mathbf{y})q(k', \boldsymbol{\theta}_{i=k'})}\right).$$

If accepted,

- Sample $\mathbf{s}|\mathbf{y}, \boldsymbol{\tau}, \boldsymbol{\beta}, \eta, \mathbf{P}$
- Sample $\boldsymbol{\beta}|\boldsymbol{\tau}, \eta, \mathbf{y}, \mathbf{s}, \mathbf{P}$
- Sample $\mathbf{P}|\mathbf{y}, \boldsymbol{\tau}, \boldsymbol{\beta}, \eta, \mathbf{s}$
- Sample $\eta|\boldsymbol{\beta}, \mathbf{y}, \boldsymbol{\tau}, \mathbf{s}, \mathbf{P}$
- Sample $\boldsymbol{\tau}|\eta, \boldsymbol{\beta}, \mathbf{y}, \mathbf{s}, \mathbf{P}$

Otherwise, go to the first step.

Postestimation Inference Using Transition Covariates

Previous applications of changepoint models have centered on detecting unknown breaks in time-series data. However, researchers would often like to study the causes of these structural changes. This section will illustrate a simple technique for exploring the determinants of structural changes using the simulation outputs of changepoint models.

The MCMC sampling of the changepoint model generates posterior samples of state probabilities that contain updated information about the probabilities of each state at each time period.

$$\Pr(s_t|\mathbf{y}) = \int_{\Theta} p(s_t = i|\mathbf{y}, \boldsymbol{\theta}, \mathbf{P})\, p(\boldsymbol{\theta}, \mathbf{P}|\mathbf{y})\, d(\boldsymbol{\theta}, \mathbf{P}) \quad (3)$$

where $\mathbf{y}$ is data, $\boldsymbol{\theta}$ is a regression model-specific parameter vector, and $\mathbf{P}$ is a transition matrix. The first-difference of posterior state probabilities between adjacent states provides posterior samples of regime change probability at each period. We can use the regime change probability, $\Pr(\text{Break}\,|\,\mathbf{y})$, to make inferences about causes of structural changes. Generally speaking, when there are M breaks, the regime change probability into regime j at t can be defined as follows:

$$\Pr(\text{Break}_t^j|\mathbf{y}) = \max\left\{\Pr(s_t = j+1|\mathbf{y}) - \Pr(s_{t-1} = j+1|\mathbf{y}), 0\right\} \quad \text{for} \quad j = 1 \ldots M$$

It is important to note that independent variables used in this regression analysis should be exogenous to regime changes, which I call transition covariates in this article. Then, the conditional probability for a regime change can be written as a linear function of transition covariates, and estimated parameters show the association between the probability of a regime change and transition covariates.[10]

The above regression analysis tests whether there exists an *instantaneous* relationship between changes in the probability of regime changes and changes in transition covariates. However, the regime change can be caused by past events. In other words, the lack of an instantaneous correlation does not necessarily mean the lack of association in time-series data. The Granger causality test examines whether the previous values of one series are useful in predicting the values of the other series (Granger 1969; Sims 1972). In cases of multiple transition covariates, one could find it useful to use vector autoregression models for the test.

Historical Changes in U.S. Presidents' Use of Force

The empirical analysis of historical changes in U.S. presidents' use of force abroad proceeds as follows. First, I build a decision model that explains the effects of domestic and international conditions on presidents' decisions to deploy troops abroad. The decision model will be connected to a Poisson regression model. Next, I implement an exploratory data analysis of the use of force data using a Poisson changepoint model and a Poisson state space model. I then employ a Poisson regression changepoint model coupled with data augmentation and transdimensional MCMC methods to detect the existence of time-varying relationships in parameters of the decision theoretic model.

[10]In the context of the Markov switching model, Kim, Piger, and Startz (2008) directly model the effects of transition covariates on regime changes. They account for the endogeneity of transition covariates by considering the transition error in the Markov switching process to be correlated with the error process in the observed data. I appreciate one of the anonymous reviewers for pointing this out.

A Random Utility Model for the Use of Force

I begin by simplifying a wide range of factors affecting presidential decisions on military intervention into two groups. The first group denoted by **x** consists of covariates, the effects of which on the use of force are *endogenous* to structural changes. Some examples here include the popularity of presidents, the condition of the domestic economy, government partisanship, the form of government, the level of partisan support in Congress, and election cycles. The second group contains factors (**z**), the effects of which are *exogenous* to structural changes in presidential decisions to use force. Some examples include the level of international tension, the distribution of military capabilities, and the level of economic interdependence among major powers.

Using these two groups of factors, I construct a random utility model for presidents' decisions to initiate military interventions with potential structural breaks in decision rules. Let s be an arbitrary time unit within which presidents are exposed to a *binary* decision of military intervention. Let $u_s^{(I)} = f(\mathbf{x}_s, \mathbf{z}_s) + \delta_s^{(I)}$ be the utility to a president at s of military intervention (I), and $u_s^{(N)} = g(\mathbf{x}_s, \mathbf{z}_s) + \delta_s^{(N)}$ be the utility to a president at s of nonintervention (N). The functions $f(\cdot)$ and $g(\cdot)$ are unknown utility functions for presidents. The $\delta_s^{(I)}$ and $\delta_s^{(N)}$ terms are uncorrelated Gaussian disturbances with a mean of zero and a constant variance, respectively. A president decides to send military forces to a certain target only when the utility of military intervention is larger than nonintervention: $u_s^{(I)} > u_s^{(N)}$. We can construct a random utility model related with **x** and **z** by arranging the utility difference as follows:

$$\begin{aligned} u_s^{(I)} - u_s^{(N)} &= \left[f(\mathbf{x}_s, \mathbf{z}_s) + \delta_s^{(I)}\right] - \left[g(\mathbf{x}_s, \mathbf{z}_s) + \delta_s^{(N)}\right] \\ &= [f(\mathbf{x}_s, \mathbf{z}_s) - g(\mathbf{x}_s, \mathbf{z}_s)] + \left[\delta_s^{(I)} - \delta_s^{(N)}\right] \\ &= q(\mathbf{x}_s, \mathbf{z}_s) + \varepsilon_s \end{aligned}$$

Then, a realization of a decision ($I_s = 1$) to deploy troops abroad within the time interval of s follows the Bernoulli process, and its aggregation into a larger time unit t follows the Poisson process.[11] Let t_s be the total number of s in a t interval and $h(\cdot)$ be a monotonic transformation of $q(\cdot)$. Then, the sum of binary decisions within a constant time interval can be modeled as a Poisson regression model.

[11]For the connection between binary choice models and Poisson models, see Cameron and Trivedi (1998) and Alt, King, and Signorino (2001).

$$I_s = \begin{cases} 1 & \text{if} \quad u_s^{(I)} - u_s^{(N)} > 0 \\ 0 & \text{if} \quad u_s^{(I)} - u_s^{(N)} \le 0 \end{cases}$$

$$y_t = \sum_{i=1}^{t_s} I_i$$

$$y_t \sim \mathcal{P}oisson(\lambda_t), \quad \lambda_t = \exp(h(\mathbf{x}_t, \mathbf{z}_t))$$

Finding the association between **y** and **x** in a Poisson regression model with constant parameters is a daunting task because it is difficult to fully account for the factors causing structural changes (**z**) and we do not know the relationship between **x**, **z**, and **y**. This inferential difficulty is well known to scholars in the study of use of force (e.g., Meernik and Waterman 1996; Meernik 2000). The problem is caused by constant parameter models that cannot estimate the relationship between **y** and **x** without properly including **z** in the regression model. However, if the effects of the factors causing structural changes (**z**) on **x** and **y** can be well approximated by regime-dependent relationships, changepoint models can estimate the time-varying relationship between **y** and **x** without including the factors causing structural changes (**z**). In the following paragraphs, I will list covariates that will be included in **x** in the analysis.

Former studies of use of force show that Congress plays an important role in presidential decisions to use force abroad. For example, employing the use of force data from 1949 to 2000, Howell and Pevehouse (2005) show that the size of a president's party in Congress is positively correlated with the frequency of the use of force. I include a dummy variable indicating divided government to estimate whether the type of party control of government has a time-varying effect on presidential decisions to use force abroad. Also, I include separate levels of partisan support in the House and in the Senate to check whether the Senate plays a different role from the House in foreign policymaking.

Two measures of economic conditions—growth rates and unemployment rates—are included to capture the effects of the domestic economy. The yearly aggregation of use of force data and the uncertainty surrounding present economic conditions are two complications for a researcher to consider. For instance, the use of force in January could be affected by economic conditions measured at the end of the previous year. Thus, the measures of economic conditions are lagged by one year to avoid possible post-treatment effects. Because pre-1890 unemployment data are not available, the sample period starts at 1890 and ends in 1995. The source of unemployment data is the same as in Fordham (2002).

I also include two dummy variables indicating the Great Depression (1929–39) and the two world wars (1914–18; 1939–45). These dummy variables are inserted to capture the *instantaneous* effects of two critical events on the U.S. presidents' decisions to use force abroad. These two critical events are expected to discourage U.S. presidents from using military force abroad. However, any *long-term* or *persistent* effects generated by these critical events on presidential decisions to use force abroad will be captured as parametric shifts by changepoint models.

- `Divided`: A dummy variable indicating divided government
- `Senate`: The seat share of the presidential party in the Senate
- `House`: The seat share of the presidential party in the House
- `Growth`: The GDP growth rate lagged by one year
- `Unemployment`: The unemployment rate lagged by one year
- `Depression`: A dummy variable indicating the Great Depression (1929–39)
- `World War`: A dummy variable indicating World War I and World War II.

Exploratory Data Analysis Using a Poisson State Space Model

To explore the time-varying movements in the parameters of the selected covariates, I implement exploratory data analysis using a Poisson state space model. State space models are related to changepoint models because observed data are generated by latent states in both models, and the effects of latent states are captured by time-varying parameters. However, unlike changepoint models, parameters change at every time period in state space models. In other words, the number of states is the same as the total number of observations ($m = T$) in state space models. Thus, a state space model can be understood as a special type of changepoint model, most suitable in cases where parametric changes are frequent and the process is evolutionary.[12]

Figure 2 illustrates the results of the Poisson state space model. Most parameters of domestic conditions have gone through dramatic changes. For example, the effect of divided government on the frequency of the use of force abroad by U.S. presidents is positive during the first half of twentieth century, but disappears after the 1950s. Second, the effect of partisan support in each legislative chamber moves in opposite directions. In the Senate, more members of the president's party lead to more military actions; in the House, greater levels of opposition lead to more military strikes. I will offer a potential interpretation in the next section. Third, the effect of unemployment follows a similar pattern to that of partisan support in the Senate. After the 1930s, presidents tend to use force more frequently as unemployment rises; before, no clear relationship exists. Overall, the findings of the Poisson state space model illustrate that the character of the dynamic process in the use of force model seems appropriate for changepoint analysis in that parameters change only a couple of times within the sample period. This type of infrequent regime changes can be effectively estimated by changepoint models.

Despite these telling results, the large amount of parameter uncertainty in the Poisson state space model makes it difficult to use them in statistical decisions such as hypothesis testing. Uncertain estimates in the Poisson state space model are the price we have to pay in order to have the flexibility of time-varying parameters. Given the trade-off, it would be useful to find a method to *choose the optimal number of parameter changes* by penalizing the complexity of the model while rewarding its predictive power. The changepoint analysis introduced in this article does just that.

Changepoint Analysis of the Use of Force Model

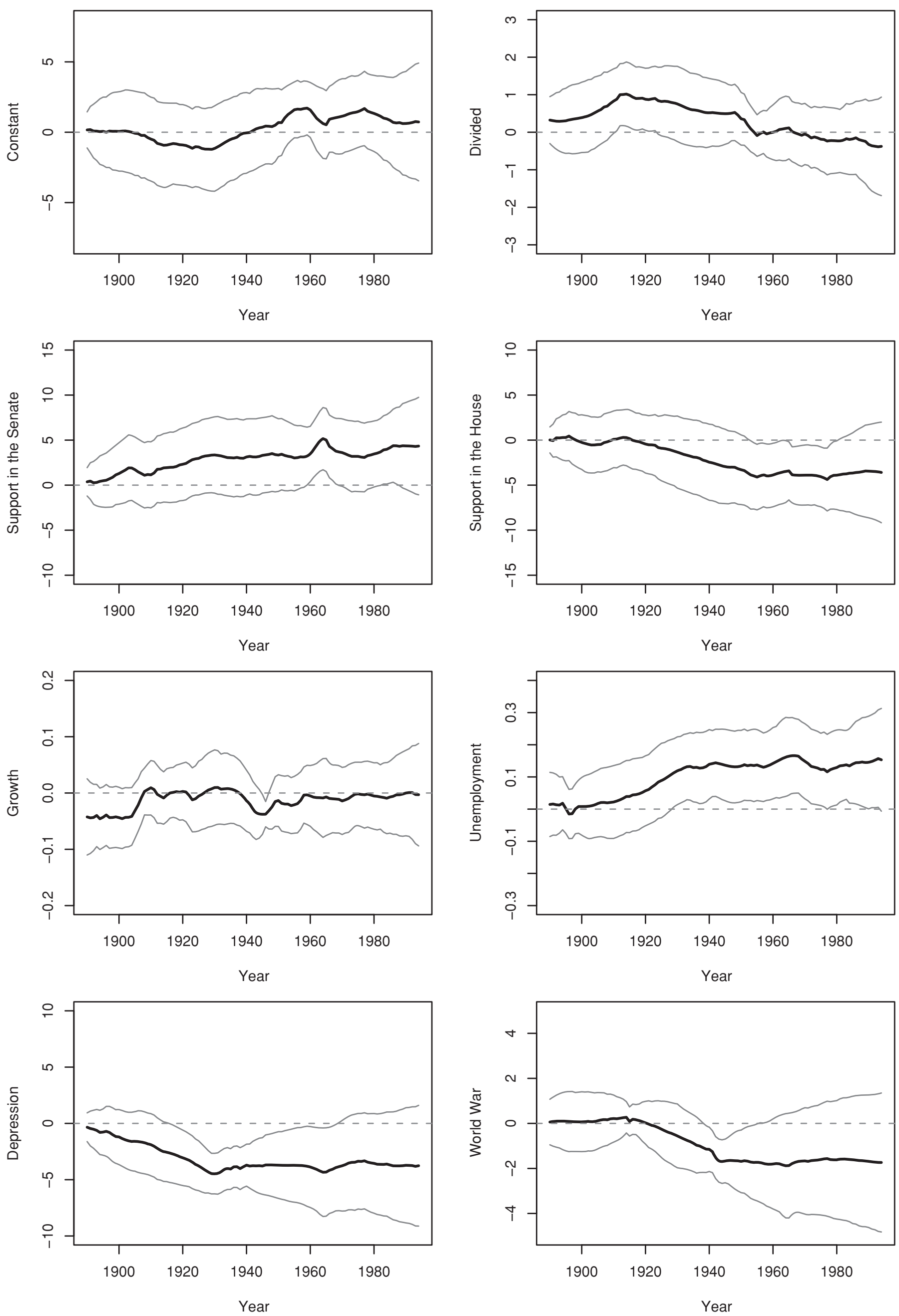
I now fit the Poisson regression changepoint model to the use of force data with the selected covariates. I choose uninformative Gaussian distributions as the priors for slope parameters: $\beta_k \sim \mathcal{N}(0, 100)$. For transition probabilities I use the Beta distributions that reflect the equidistant duration of each state given the number of states in each model. For example, in the one-changepoint case, one-half of the total sample period (126 years) is 63. Thus, I use $\mathcal{B}eta(6.3, 0.1)$ for the one-changepoint model, $\mathcal{B}eta(4.2, 0.1)$ for the two-changepoint model, $\mathcal{B}eta(3.2, 0.1)$ for the three-changepoint model, and $\mathcal{B}eta(2.5, 0.1)$ for the four-changepoint model.

[12] I use Frühwirth-Schnatter and Wagner's (2006) algorithm for a Poisson state space model.

$$\begin{aligned} &\text{Observation equation:} && \log \tau_{tj,n_t} - m_{r_{tj,n_t}} = -\mathbf{x}_t'\boldsymbol{\beta}_t + \nu_t,\ \ \nu_t \sim \mathcal{N}(\mathbf{0}, \mathbf{V}) \\ &\text{Transition equation:} && \boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \omega_t,\quad \omega_t \sim \mathcal{N}(\mathbf{0}, \mathbf{W}) \\ &\text{Initial condition:} && (\boldsymbol{\beta}_0 | \mathbf{D}_0) \sim \mathcal{N}(m_0, \mathbf{C}_0) \end{aligned}$$

where error terms ν_t and ω_t are mutually independent and $\mathbf{x}$ denotes exogenous variables. $\mathbf{V}$ is constructed from the estimated component indicators of the five Gaussian mixture distributions.

FIGURE 2 Results from Poisson State Space Model



Note: Dark lines in the middle are expected values and bright lines are 68% Bayesian credible intervals.

Table 1 reports the results of transdimensional MCMC runs for five candidate models.[13] To check the sensitivity, I report transdimensional MCMC results from five different proposal functions for the model indicators

[13]I use multivariate Gaussian distributions with mean and variance obtained from 1,000 initial MCMC runs for proposal densities of $\boldsymbol{\beta}$. Diagonal elements of variance-covariance matrices are multiplied by 5 for quick convergence. Also, for proposal densities of transition probabilities, I obtained parameter values of the Beta distributions from 1,000 initial MCMC runs. I employ a discretized Laplacian density with a 0.4 shape parameter for model space jump proposals. Based on the results of exploratory analysis in the previous section, I set the upper bound for the number of changepoints at 4.

TABLE 1 Transdimensional MCMC Runs for Five Poisson Changepoint Models

λ	$\mathcal{M}_0$	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$
0.03	1910	63808	21207	9302	3773
0.10	2935	57076	21420	10900	7669
0.40	2352	57586	22953	9724	7385
0.50	1714	56690	22740	12388	6468
0.90	1609	58372	23037	10970	6012

Note: Transdimensional MCMC chains are run 100,000 times. Posterior model probabilities can be computed by dividing the number of acceptances by the total number of iterations (100,000). The one-break model is considered the most probable model when we compare five models. Five different discretized Laplacian densities are tried by varying λ from 0.03 to 0.9. The discretized Laplacian density takes the following form: $\exp(-\lambda|k' - k|), \quad k \in 0, \ldots, 4$. I choose multivariate Gaussian distributions with mean and variance obtained from 1,000 initial MCMC runs for proposal densities of $\boldsymbol{\beta}$. Diagonal elements of variance-covariance matrices are multiplied by 5 for quick convergence. I choose the beta distribution with two positive shape parameters obtained from 1,000 initial MCMC runs for the proposal densities of transition probabilities.

in each row. The numbers in each cell indicate the number of accepted proposals for each model in each trial out of 100,000 transdimensional MCMC runs. Thus, posterior probabilities of each model can be computed by dividing these numbers by 100,000.

Table 1 clearly shows that in all cases, the posterior probability of the one-changepoint model, $\Pr(\mathcal{M}_1|\mathbf{y})$, is twice as high as that of the two-changepoint model, $\Pr(\mathcal{M}_2|\mathbf{y})$. The posterior probabilities of the other models are all very low.[14] These results are consistent with results from the marginal likelihood method reported in Table 2. The natural log Bayes factor between the one-changepoint model and the two-changepoint model is 1.24. According to the Jeffrey's scale, this level of evidence in favor of the one-changepoint model over the two-changepoint model is "barely worth mentioning." While both methods of Bayesian model comparison work well in uncovering highly unrealistic models, transdimensional MCMC methods allow us to make more accurate assessments of model uncertainty among relatively reasonable models.

The estimated breakpoint and the probability of the structural break are displayed in Figure 3. The posterior probability of the regime change, which is displayed in the right panel of Figure 3, indicates that the regime change was quite quick and dramatic. Specifically, the 95% probability density falls between 1930 and 1953 with the expected timing of 1942.[15] Interestingly, the attack on Pearl Harbor—December 7, 1941—is at the center of the regime transition in U.S. presidents' use of force. According to Gaddis, "Pearl Harbor was . . . the defining event for the American empire, because it was only at this point that the most plausible potential justification for the United States becoming and remaining a global power . . . became an actual one. Isolationism . . . suffered a blow from which it never recovered. The critical date was not 1945, or 1947, but 1941" (1997, 35–36).

In order to investigate the character of the regime change in detail, I compare the posterior distributions of parameter estimates from the Poisson regression changepoint model with those from the Poisson regression model with no break in Figure 4. The no-break line indicates the estimates of the constant Poisson regression model, and the "Prebreak" and the "Postbreak" lines indicate parameter estimates from the prebreak regime and the postbreak regime, respectively.[16]

Most strikingly, the effects of partisan support in Congress and the effect of unemployment on the frequency of the use of force completely disappear when we do not consider the existence of the structural break, as shown by dotted lines in Figure 4.[17] This is one of the reasons why Gowa (1998) could not find statistically significant effects of domestic conditions on the use of force when she extended the data frame into 1870. Aware of historical changes, Gowa (1998) uses two time dummy variables that capture historical changes in the role of the United States in the international system. One is between 1898 and 1949 when the United States was a major power and the other is between 1949 and 1992 when the United States was a superpower. However, she does not interact these dummy variables with any of her explanatory variables. By not doing so, these structural changes are constrained to affect only the baseline level of the use of force without being allowed to capture any structural change in the relationship between domestic conditions and the frequency of the use of force abroad. Overall, the

[14] Although the two-changepoint model has weak support from the data as reported in Table 1, the first break in the two-changepoint model is estimated at the beginning of the sample period (1891) while the second break coincides with the break in the one-break model. Thus, two models provide a substantively similar conclusion.

[15] The 95% Bayesian credible intervals for regime shifting timing are computed by finding the highest posterior density region in the density of changepoint probabilities.

[16] Note that these two sets of parameter estimates from the changepoint model are different from parameter estimates obtained with a time dummy variable or with separate regressions after dividing samples into two groups. The estimates from the changepoint model fully reflect the probabilistic inference on the regime change utilizing the observed data, while thosefrom a dummy variable or separate regressions are based on deterministic knowledge about the regime change, which comes purely from researchers' prior beliefs.

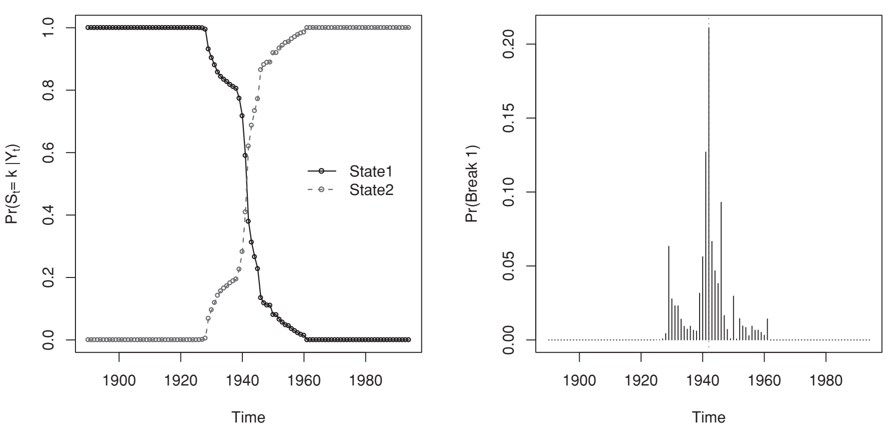
[17] The parameter estimates are reported in Table 3.

TABLE 2 Changepoint Model Comparison of Poisson Changepoint Models on the Domestic Model of the Use of Force Abroad

	$\mathcal{M}_0$	$\mathcal{M}_1$	$\mathcal{M}_2$	$\mathcal{M}_3$	$\mathcal{M}_4$	$\mathcal{M}_5$	$\mathcal{M}_6$	$\mathcal{M}_7$	$\mathcal{M}_8$	$\mathcal{M}_9$
$\mathcal{M}_0$	0.0	−48.55	−47.30	−45.85	−44.32	−42.82	−41.23	−39.37	−37.96	−36.57
$\mathcal{M}_1$	48.5	0.00	1.24	2.70	4.23	5.72	7.31	9.17	10.58	11.98
$\mathcal{M}_2$	47.3	−1.24	0.00	1.46	2.99	4.48	6.07	7.93	9.34	10.73
$\mathcal{M}_3$	45.8	−2.70	−1.46	0.00	1.53	3.02	4.61	6.48	7.88	9.28
$\mathcal{M}_4$	44.3	−4.23	−2.99	−1.53	0.00	1.49	3.09	4.95	6.35	7.75
$\mathcal{M}_5$	42.8	−5.72	−4.48	−3.02	−1.49	0.00	1.59	3.45	4.86	6.25
$\mathcal{M}_6$	41.2	−7.31	−6.07	−4.61	−3.09	−1.59	0.00	1.86	3.27	4.66
$\mathcal{M}_7$	39.4	−9.17	−7.93	−6.48	−4.95	−3.45	−1.86	0.00	1.41	2.80
$\mathcal{M}_8$	38.0	−10.58	−9.34	−7.88	−6.35	−4.86	−3.27	−1.41	0.00	1.39
$\mathcal{M}_9$	36.6	−11.98	−10.73	−9.28	−7.75	−6.25	−4.66	−2.80	−1.39	0.00

Note: The number in the cell (i, j) indicates $\log(m(\mathbf{y}|\mathcal{M}_{i-1})) - \log(m(\mathbf{y}|\mathcal{M}_{j-1}))$. According to Jeffreys (1961), if the natural log Bayes factor is larger than 1, then the model in the *i*th row is preferred to a model in the *j*th column. The model favored by the Bayes factor is highlighted. MCMC chains are run 10,000 times after discarding the first 10,000 draws.

FIGURE 3 Posterior State Probabilities of the One-Changepoint Model

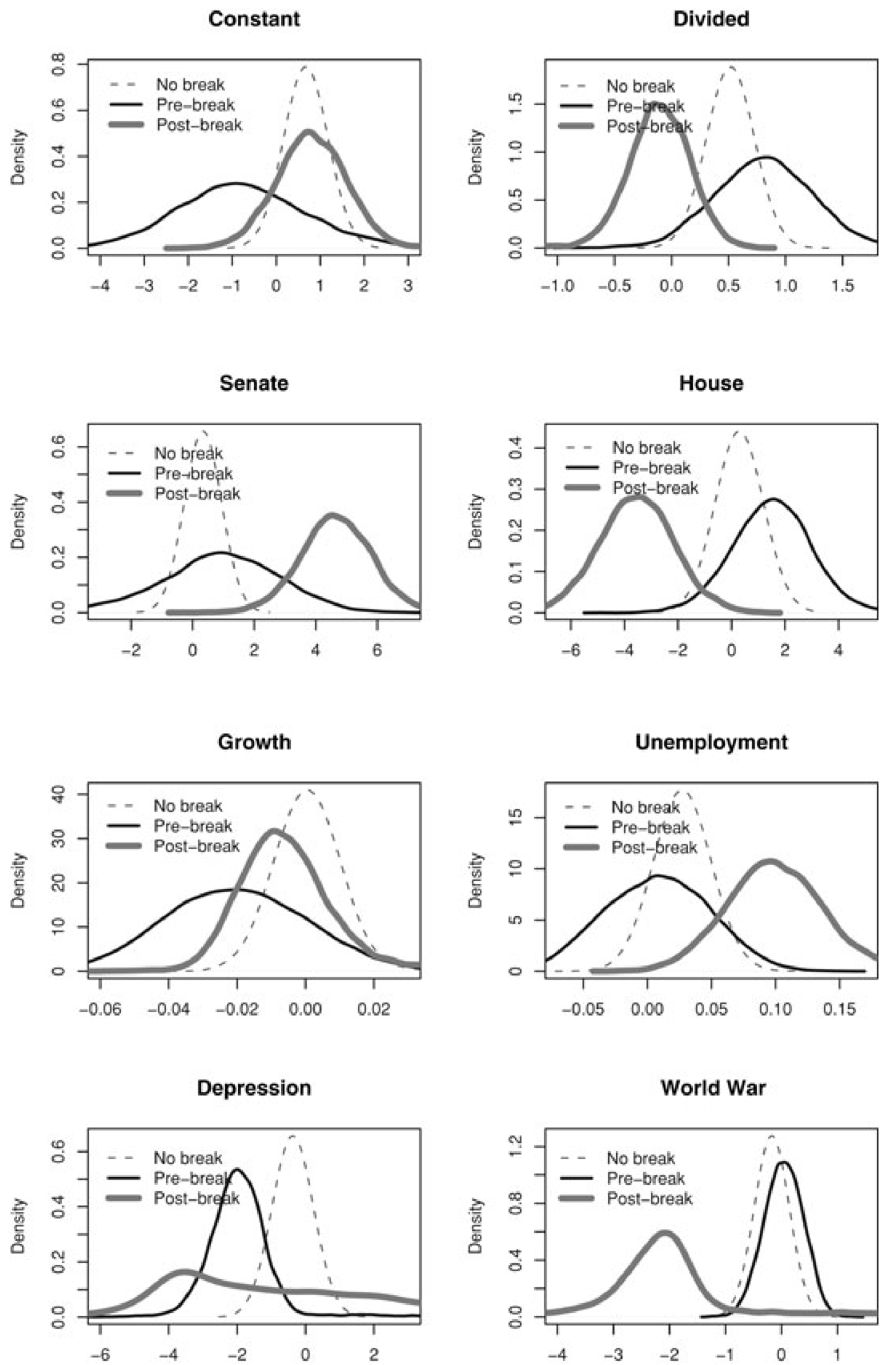


Note: The dark line in the left panel indicates posterior probabilities of state 1, and the bright line in the left panel indicates posterior probabilities of state 2. The expected breakpoint (the dotted line in the right panel) is 1942 with the 95% highest posterior density falling between 1930 and 1953. The prebreak mean is 1.85 and the postbreak mean is 7.22. The right panel shows the posterior probability of a regime change.

findings in Figure 4 demonstrate that there was a structural change in the relationship between domestic factors and the frequency of the use of force, controlling for the effects of the Great Depression and the two world wars.

Second, the effects of partisan support in Congress on the frequency of the use of force are significantly different, not just across time but also between chambers. These time-varying interchamber differences are quite robust to different model specifications and to the use of alternative measures of partisan support in Congress. The most puzzling finding is the *negative* effect of the partisan support for presidents in the postbreak House. Even though I do not aim to provide a full answer to this puzzle here, I interpret the postbreak interchamber difference to be a consequence of electoral forces that generated interventionist presidents who won office in a landslide, specifically Lyndon Johnson and Ronald Reagan. These big victories helped copartisan candidates in Senate races, while most House incumbents successfully distanced themselves from unfavorable national conditions. For example, in the 1980 elections, the Republican presidential challenger, Ronald Reagan, fiercely attacked Carter's mismanagement of the Iran hostage crisis and won a decisive victory with additional help from the

FIGURE 4 Comparison of Parameter Estimates from the Poisson Regression Changepoint Model and the Poisson Regression Model



Note: No break lines show posterior distributions of the Poisson regression model estimated by a random walk Metropolis-Hastings algorithm using Martin, Quinn, and Park (2008). Prebreak and Postbreak lines indicate parameter estimates of the Poisson regression changepoint model for the prebreak regime and for the postbreak regime, respectively. The expected breakpoint (the dotted line) is 1942, with the 95% highest posterior density falling between 1930 and 1953.

TABLE 3 Parameter Estimates of the Use of Force Abroad with One Break

	Pre-1942				Post-1942			
	Mean	St. Dev.	Lower	Upper	Mean	St. Dev.	Lower	Upper
Constant	−0.781	1.439	−3.529	2.185	0.811	0.814	−0.771	2.395
Divided	0.810	0.426	−0.010	1.647	−0.110	0.272	−0.660	0.398
Senate	0.906	1.913	−3.098	4.475	4.655	1.144	2.358	6.887
House	1.498	1.464	−1.439	4.388	−3.552	1.400	−6.329	−0.748
Growth	−0.020	0.021	−0.059	0.021	−0.005	0.016	−0.029	0.037
Unemployment	0.007	0.042	−0.073	0.087	0.100	0.038	0.029	0.175
Depression	−1.868	1.219	−3.587	1.368	−0.943	3.105	−5.694	5.686
World War	0.039	0.351	−0.655	0.694	−1.720	1.874	−4.280	3.939

Note: St. Dev. indicates the standard deviation, and Lower and Upper indicate two boundaries of 95% Bayesian credible intervals. MCMC chains are run 10,000 times after discarding the first 10,000 draws.

sluggish domestic economy. Reagan's party won 12 additional Senate seats and became the majority party in the Senate for the first time since 1952. However, the Republican party did not attain a majority in the House. The Republicans added only 34 seats in the House, for a total of 192 seats. In other words, despite the national swing favoring the Republican party, House Democrats successfully defended their majority by securing 242 seats. After taking office, Reagan used force abroad twice as often as Carter did: the annual average of the number of uses of force under the Reagan administration was 10.5 while the annual average under the Carter administration was 5.

Third, the positive effect of unemployment on the frequency of the use of force abroad, which has been suggested as important evidence for the diversionary hypothesis in previous studies on the use of force (Fordham 1998a, 1998b, 2002; Howell and Pevehouse 2005), is found to exist only after the structural break in the 1940s. That is, the tendency to use force more frequently under high unemployment rates exists only for postwar U.S. presidents.

Lastly, the effect of divided government on presidential decisions to use force is positive up until the break. Afterwards, the decision to execute military ventures has not been hampered or encouraged by a partisan split in the two chambers.

Alternative model specifications excluding one political variable at a time provide substantively similar results. For example, the opposing signs for the Senate and House do not disappear whether or not *Divided* is included in the model. The direction of the signs in *Senate* and *House* remain the same even if one of the variables is dropped. The statistical insignificance of *Divided* after the break remains consistent with alternative model specifications. Also, the findings are not sensitive to the choice of prior values.[18]

What Caused the Structural Change?

In this section, I investigate whether the structural change in U.S. presidents' foreign policy decisions is caused by factors suggested by Waltz's structural theory of international politics. Waltz argues that foreign policy decision making by each state is subject to three primary system-level factors: (1) the ordering principle of the international system, the anarchy, (2) the goal of state, survival, and (3) the distribution of capabilities (Waltz 1979). The first two factors define the modern international system and consequently do not change within the modern international system. In contrast, the third factor, the distribution of capabilities, changes within the system, generating different subsystems over time, such as multipolar system or bipolar system.

The hypothesis tested in this analysis is that the dramatic change in presidential decisions to use force abroad was caused by changes in the distribution of capabilities in the international system. The dependent variable is the posterior regime change probability from the change-point analysis, and the distribution of capability is operationalized by the concentration of military capability into the United States and the Soviet Union in the international system. The military capability is measured by the Composite Index of National Capability score provided by

[18]The results of the prior sensitivity analysis are available at the web appendix.

TABLE 4 Determinants of the Structural Break in U.S. Presidents' Decision to Use Force

Regression Analysis (OLS)		
	Mean	**SE**
Constant	0.989	0.260
ΔNon-U.S. MID	−0.042	0.021
ΔCapability	0.374	0.126
RMSE	0.0265	
R^2	0.0970	

Note: The dependent variable is the posterior probability of the structural break in U.S. presidents' use of force, which ranges from 0 to 100. All explanatory variables are first-differenced. The ordinary least-squares method is used for the estimation. SE indicates the standard error. Δ indicates the first-differencing. Non-U.S. MID is the number of militarized interstate disputes not involving the United States, which ranges from 0 to 87 in the data. Capability is the share of military capabilities by the United States and the Soviet Union (Russia) in the world's total military capability. Capability ranges from 13.08 to 38.38 in the data.

Ghosn, Palmer, and Bremer (2001).[19] To avoid the spurious correlation that would result from regressing trended data, the explanatory variables are also first-differenced.

Another system-level factor that may affect presidential decisions about force is the overall level of international disputes. Changes in the frequency of international disputes may indicate changes in opportunities of military interventions by U.S. presidents. Increasing military strikes after the 1940s may reflect changes in the frequency of international disputes. The data on the number of militarized interstate disputes are obtained from Ghosn, Palmer, and Bremer (2001). However, in accounting for international disputes, we should exclude the ones involving the United States to avoid endogeneity. I include the frequency of international disputes excluding ones involving the United States (*Non-U.S. MID*) as another transition covariate.

The results of ordinary least-squares analysis on the determinants of a regime change are summarized in Table 4. All transition covariates are statistically significant at the 95% level. Controlling for the effect of changes in opportunities of the use of force, the concentration of military capability by the United States and the Soviet Union increases the probability of the regime change in U.S. presidents' decision rules about force. However, it is strange to observe a negative effect of Δ*Non-U.S. MID*

TABLE 5 The Granger Causality Test

	F-statistic	**p-value**
ΔCapability → Pr(Regime Change)		
Lag 1	2.39	0.13
Lag 2	1.55	0.22
Lag 3	1.15	0.33
Lag 4	1.49	0.21
Lag 5	0.93	0.47
Pr(Regime Change) → ΔCapability		
Lag 1	3.73	0.06
Lag 2	2.71	0.07
Lag 3	1.70	0.18
Lag 4	1.74	0.15
Lag 5	2.29	0.06
ΔNon-U.S. MID → Pr(Regime Change)		
Lag 1	0.00	0.96
Lag 2	5.82	0.00
Lag 3	8.13	0.00
Lag 4	5.86	0.00
Lag 5	5.29	0.00
Pr(Regime Change) → Δ Non-U.S. MID		
Lag 1	4.44	0.04
Lag 2	3.40	0.04
Lag 3	2.04	0.11
Lag 4	1.36	0.26
Lag 5	1.05	0.40

Note: The null hypothesis of the Granger causality test is no predictive power of lagged x in predicting lagged y. The Granger causality test is done by `granger.test` in `MSBVAR` package. Δ indicates the first-differencing. Non-U.S. MID is the number of militarized interstate disputes not involving the United States, which ranges from 0 to 87 in the data. Capability is the share of military capabilities by the United States and the Soviet Union (Russia) in the world's total military capability. Capability ranges from 13.08 to 38.38 in the data.

on the probability of the regime change given the nature of the break from isolationism to interventionism. Thus, I check whether changes in military capabilities are *causally prior* to the probability of the regime change using the Granger causality test.[20]

Table 5 reports the results of the bivariate Granger causality test. The first two panels show that, regardless of the lag specification, there is not enough evidence to

[19]The capability score measures annual values of total population, urban population, iron and steel production, energy consumption, military personnel, and military expenditure of all state members (Singer 1987).

[20]I chose the Granger causality test because the interpretation of the results is simple and intuitive. The results from vector autoregression models provide the same conclusion as the bivariate Granger causality test.

conclude that changes in *Capability* are causally prior to the regime change probability. In contrast, there is evidence that changes in the frequency of international disputes, excluding those involving the United States, are causally prior to the regime change probability when three-year lags are taken into account.[21]

Conclusion

In this article, I present an integrated Bayesian approach for analyzing changepoint problems in a Poisson regression model. This approach integrates (1) transdimensional MCMC methods for model selection, (2) Frühwirth-Schnatter and Wagner's (2006) data augmentation method using hidden interarrival times, and (3) postestimation analysis of the causes of structural changes using posterior draws of hidden states. This integrated Bayesian approach turns out to be highly effective in uncovering historically contingent relationships in event-count data. In the use of force example, I found that there was a structural break in the way U.S. presidents use force abroad around 1940. The findings of the article shed new light on the literature in several ways.

First, the estimated breakpoint in the 1940s is obtained after we account for the effect of domestic conditions and the immediate effects of the Great Depression and the two world wars on presidents' decisions to use force abroad. A sophisticated statistical model is essential to find the number, location, and characteristics of structural breaks, while also accounting for the effects of selected covariates.

Second, the findings of the article discover regime-dependent effects in several covariates of the use of force. Specifically, the partisan support for presidents in Congress has different effects on presidents' decisions to send military troops abroad before and after the structural break. Also, the effect of the partisan support is positive in the postbreak Senate, but negative in the postbreak House. The positive effect of unemployment on the frequency of use of force, which has been suggested as important evidence for the diversionary hypothesis by previous literature (Fordham 1998a, 1998b, 2002; Howell and Pevehouse 2005), is found to exist only after the structural break in the 1940s.

Last, the findings of the article resolve a previous debate about the sensitivity of domestic factors' statistical significance to the researcher's choice of a contemporary or extended historical time frame (e.g., Gowa 1998; Fordham 2002). The changepoint analysis of the use of force data shows that the effects of domestic conditions are not time constant between 1890 and 1995. Extending the time frame increases the sample size as well as the heterogeneity of the data. When researchers pool historical data without checking for structural breaks, they ignore the potential for different groupings of data-generating processes and risk reaching erroneous conclusions.

[21]See the web appendix for the graphical display of the lagged effects.

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