Economic development, population and civil war: a Bayesian changepoint model

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Abstract

Purpose – This study proposes a Bayesian approach to analyze structural breaks and examines whether structural changes have occurred, at the onset of civil war, with respect to economic development and population during the period from 1945 to 1999.

Design/methodology/approach – In the Bayesian logit regression changepoint model, parameters of covariates are allowed to shift individually, regime transitions can move back and forth, and the model is applicable to cross-sectional, time-series data.

Findings – Contrary to popular belief that the causal process of civil war changed with the end of the Cold War, the empirical analysis shows that the regression relationships between civil war and economic development, as well as between civil war and population, remain quite stable during the study period.

Originality/value – This is the first to develop a Bayesian logit regression changepoint model and to apply it to studies of economic development and civil war.

Keywords Economic development, Population, Structural changes, Bayesian logit regression changepoint model, Civil war

Paper type Research paper

1. Introduction

When suspecting unusual changes in a political or economic phenomenon, researchers are eager to employ changepoint analysis that may enable them to identify such structural changes as well as their causes. Interesting political changes may occur during a certain time period within a country or across countries. However, existing changepoint models are designed to mainly deal with a series of time ordered data within a country (e.g., Quandt, 1960; Brown *et al.*, 1975; Andrews, 1993; Andrews *et al.*, 1996; Bai and Perron, 1998; Chib, 1998; Spirling, 2007). Since existing changepoint models can handle time-series data only, they are not appropriate to detect structural breaks that may exist in cross-national, time-series data. Most existing changepoint models are also not suitable for more than one changepoint (e.g., Quandt, 1960; Andrews, 1993; Spirling, 2007), incorporating covariates (e.g., Chib, 1998), or modification of programming codes for a new research project.

In this study, we make two contributions to the fields of economics and political science. Our primary contribution is building a new Bayesian logit regression changepoint model. The changepoint model accommodates both time-varying parameters of covariates and country-specific fixed effects. The rationale for the use of logit is that it is one of the most

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commonly used statistical models and, more importantly, it is an appropriate estimator for the research question raised in this study. It should be noted that the underlying logic and procedures of the current approach can also be extended to a large family of generalized linear models. In this study, a Bayesian method is used due to its computational advantage in handling high-dimensional parameter vectors and OpenBUGS [1] is used to implement a Metropolis–Hastings sampler based on the models and priors information specified by the authors, which saves computation time. This Bayesian changepoint estimation method for a logit model has three advantages over existing models. First, traditional changepoint models normally assume that the effects of all covariates change across different regimes; [2] however, this assumption is too restrictive since the influence of some covariates may vary between two regimes while that of the others remains the same. The model presented in this study relaxes this assumption and allows the researcher to examine the effect of each covariate separately over time. From the standpoint of policy making, being able to zero in the exact time of change associated with individual covariates of interest would be more useful with respect to making timely policy adjustments. A second consideration is that changes in regimes are not restricted to move forward and a transition between regimes can occur in both directions. Finally, the proposed method enables the researcher to investigate multiple changepoints in cross-sectional, time-series data.

Our secondary contribution is an application of the Bayesian changepoint model to the relationships among economic development, population and civil war—one of the most popular topics in the economic development and civil war literature. This application attempts to statistically identify whether there were structural breaks in the relationships during the period from 1945 to 1999. Although a common perspective among many scholars, policymakers and journalists is that the outbreak of civil wars has become widespread since the collapse of the former Soviet Union (e.g., Gellner, 1983; Huntington, 1996), there is no single empirical study that examines structural change in the incidence of civil wars in the context of a Bayesian changepoint model. Relying on a simple graphical presentation, Fearon and Laitin (2003, p. 75) demonstrate that "the current prevalence of internal war is mainly the result of a steady accumulation of protracted conflicts since the 1950s and 1960s rather than a sudden change associated with a new, post-Cold War international system." Since Fearon and Laitin's finding, which runs contradictory to the conventional wisdom, is discovered by eyeballing line plots, it warrants further investigation with a more rigorous and formal method. Furthermore, the second part of Fearon and Laitin's study reports standard logit regression results, showing evidence that economic development and population rather than political grievances are two important causes of the onset of civil war. It should be intriguing to learn whether the effects of these two factors hold up in the context of a Bayesian changepoint model.

Upon fitting a Bayesian changepoint model to Fearon and Laitin's civil war data for 156 countries during the period from 1945 to 1999, this study finds that there was no structural break in the relationship between civil war and its economic determinants (i.e., economic development and population). Moreover, since a 95% credible interval for the coefficient of economic development does not include the value zero for all the years studied, it is fair to suggest that economic issues have always been key factors in explaining the onset of internal conflict, even during the Cold War period when such issues were purposely suppressed by the rivalry of the two superpowers. The overall results of this study confirm Fearon and Laitin's findings.

2. Model building in OpenBUGS

OpenBUGS provides applied researchers with a more efficient way of conducting Bayesian analysis. While the researchers need to specify their statistical model, parameters and priors, the software will execute the codes choosing an appropriate simulation scheme based on the specified model. To render our empirical results comparable to existing research, we also adopt a logit model and estimate it with a Bayesian approach due to the computational advantage of the latter. Our Bayesian changepoint logit model is constructed as follows.

If we let y_{ik} record the occurrence or absence of civil war for country i in the kth year and follow a Bernoulli (p_{ik}), with p_{ik} denoting the probability of civil war onset for the said country in the given year, we have a logit model as follows:

$$\log\left(\frac{p_{ik}}{1-p_{ik}}\right) = \beta_{0_k} + \beta_{1_k}x_{1_{ik}} + \beta_{2_k}x_{2_{ik}} + \beta_{3_k}x_{3_{ik}} + b_i, \tag{1}$$

where $i = 1, 2, \ldots, 156$, specifying the 156 countries included in the sample and $k = 1, 2, \ldots, 55$, indexing the yearly time periods.

Let $\beta_k = (\beta_{0_k}, \beta_{1_k}, \ \beta_{2_k}, \ \beta_{3_k})'$ denote the regression coefficient vector for period k. We assume that $\beta_1, \ \ldots, \ \beta_{55}$ represent a random sample from a multivariate normal prior with mean vector μ_β and variance-covariance matrix V:

$$\beta_k | \mu_\beta, \ \ V \sim N_4(\mu_\beta, \ \ V),$$

and vague priors are assigned to the hyper-parameters:

$$\mu_\beta \sim N_4\left(0, \, I_4 \cdot 1.0E^6\right),$$

$$V \sim \text{Inverse Wishart}\left(S^{-1}, \, \upsilon\right).$$

Since OpenBUGS uses the precision matrix instead of the variance-covariance matrix as the scale parameter for normal distributions, the precision matrix $P = V^{-1} \sim \text{Wishart}(S, \, \upsilon)$. Here $\upsilon = 4$ and S is defined as $I_4 \cdot (0.1)$.

The country-specific effects b_i's are assumed to be a random sample from a normal distribution with mean zero and variance σ^2:

$$b_i \sim N\left(0, \, \sigma^2\right).$$

Similarly, in OpenBUGS, information about the variance σ^2 is represented by means of a gamma (0.01, 0.01) distribution placed on the precision τ (i.e., $(\sigma^2)^{-1}$):

$$\tau \sim \text{gamma}\,(0.01, \ 0.01).$$

3. The prevalence of civil wars and structural change

Before presenting their graphic data analysis, Fearon and Laitin (2003) provide a popular view about a historical trend of civil war outbreaks before and after the Cold War. A popular view is that there was an upsurge of civil wars since the end of the Cold War and attributes this upsurge to the evaporation of tensions from superpower rivalry that existed during the Cold War period as well as to the accompanying changes in the international system. It also suggests that because of the collapse of the Soviet Union and the subsequent relaxation of suppressive policies by the two former superpowers toward civil violence in their satellite countries, various factors which would normally drive internal wars are now left alone to play their part. In particular, political and economic issues, such as political grievances, ethnic tensions, income inequality and over-population which were deliberately downplayed during the Cold War era, appear to surface as contentious contributing factors. This line of reasoning implies that the link between civil war and its determinants is not necessarily static and that the impact of conflict-inducing factors may vary over time. Using a graphic data, Fearon and Laitin (2003, p. 75) attempt to investigate the validity of the popular belief. Fearon and Laitin discover that the recent prevalence of violent civil conflict is the result of a trend that "began immediately after Second World War." In addition, the large number of newly independent states that emerged after the Cold War might make it possible for more internal wars to occur even though the mechanism underlying their occurrence remains intact; this consideration also serves as a disincentive to aggregating civil war data into a single time series.

The discrepancy between popular belief and Fearon and Laitin's graphic presentation of the data calls for a formal test of the relationship between civil violence and its causes in the post-World War II era. If the increased level of civil violence during the post-Cold War period, as Fearon and Laitin maintain, simply resulted from a gradual accumulation of prolonged internal conflicts since the 1950s, we would not expect to observe any abrupt changes in the effects of conflict-driving forces in the years thereafter and, particularly, after the Cold War. Based on Fearon and Laitin's data collection, Figure 1 shows the annual number of countries with at least one onset of civil war during the period from 1945 to 1999. The obvious rise in the number of countries suffering a new internal conflict in the early 1990s appears to correspond with the substantial shifts in the international system. However, by merely inspecting this plot, we cannot distinguish whether this fluctuation is due to a fundamental shift in the underlying relationship between civil war and its contributing factors or just a normal outcome of the growth in independent states during that time. The observed variation warrants the construction of a proper statistical model to investigate the existence of any structural break in the mechanism of civil war.

4. Data

To examine structural changes in the causal process of civil wars, this study relies on Fearon and Laitin's dataset which is available at http://www.stanford.edu/group/ethnic/publicdata/publicdata.html. The dataset includes 156 countries during the period 1945–1999. The choice of this dataset is twofold: 1) it is the most frequently cited dataset among scholars of civil war; 2) it provides a reference point with which to compare our results.

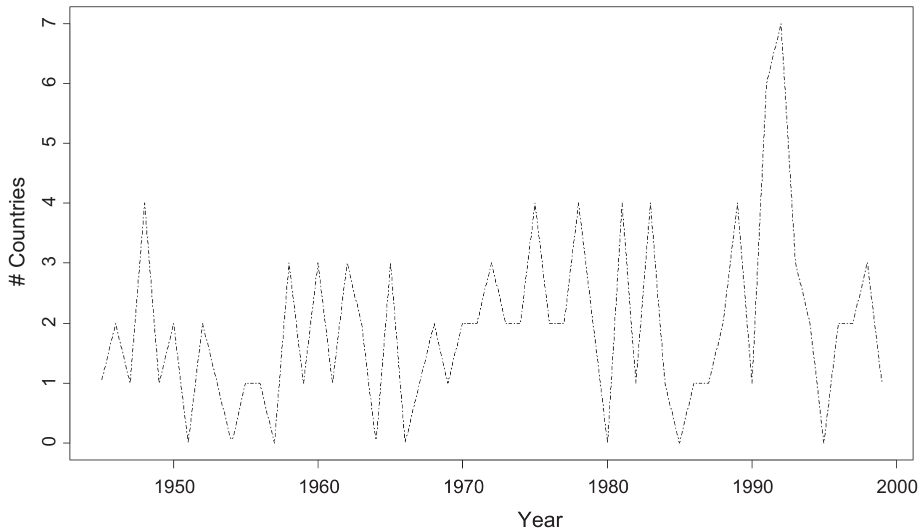


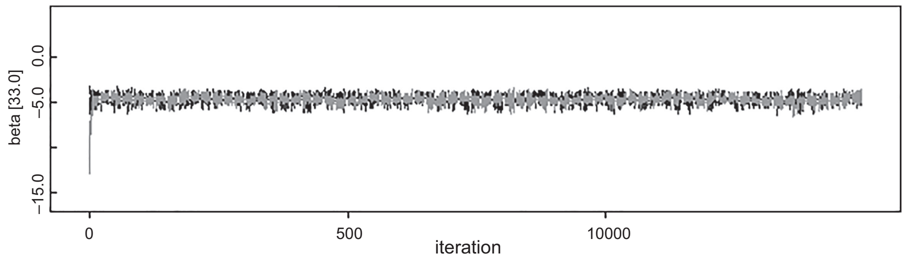
Figure 1. Number of countries with a civil war onset 1945–1999

In this study, the dependent variable is the *onset of civil wars*. It is coded as “1” for all country-years in which at least one civil war started and “0” otherwise. Fearon and Laitin’s civil war is defined as an armed conflict between agents of (or claimants to) a state and organized, sub-national groups who resort to political violence to challenge the government. The war must have caused more than 1,000 deaths in total and more than 100 deaths on both sides (including civilians attacked by rebels), with a yearly average of at least 100. The nature of a civil war can be ethnic, nationalist, or insurgent (pp. 76 and 79) [3]. The first independent variable used is economic development measured as *per capita income*. This economic variable is introduced as a proxy for the financial and bureaucratic aspects of state capacities. Countries with fragile financial, military and political institutions are more likely to experience internal wars due to weak local policing and corrupt counterinsurgency practices. Economic development is measured in thousands of 1985 U.S. dollars as collected from the Penn World Tables and World Bank data and is lagged one year to ensure that it affects the likelihood of internal war outbreak rather than vice versa. The second independent variable, *population*, is included to see whether internal wars are more likely to occur in populous countries. It is a logged term of the total population, in thousands, as gathered from World Bank figures and is also lagged one year to avoid endogeneity. In view of the possible temporal dependence between observations, a control variable, *prior war*, is added into the model. Furthermore, to speed up convergence, both the economic development and population variables are standardized to have mean zero and SD one (see OpenBUGS User Manual).

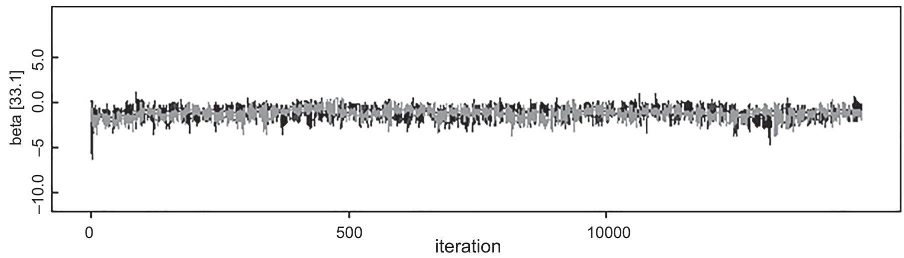
Because of the research question posed in this study and data characteristics, the logit changepoint model contains fewer explanatory variables than Fearon and Laitin’s standard logit model. Since the main purpose of this study is to test the time constancy of the impact of covariates, which are fundamental to civil strife, economic development and population are the key explanatory variables to look into. In fact, these two economically relevant variables best capture the core idea of “opportunities for insurgency” upon which Fearon and Laitin build their theory of the onset of civil war. Prior war is a control variable denoting whether or not a given country had a distinct war ongoing in the previous year. Given that the logit changepoint model also includes a term for country-specific effects, variables that have little or no temporal variations, such as mountainous terrain, noncontiguity, ethnicity, religion and being an oil exporter, are not included in the model. For the same reason, when Fearon and Laitin apply a conditional fixed effects logit to their model, they also exclude those variables (p. 87). In addition, as indicated by Fearon and Laitin’s empirical results, some variables (e.g., democracy) turn out to be statistically insignificant, so their inclusion in the logit changepoint model would be dubious; this line of reasoning will be confirmed by means of model comparison (discussed below), a common practice in Bayesian analysis for model selection.

5. Assessing convergence

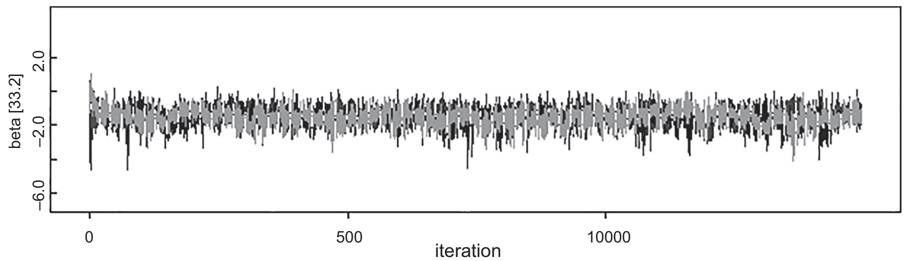
Convergence refers to the situation wherein an MCMC algorithm “has reached its equilibrium and generates values from the desired target distribution” (Ntzoufras, 2009, p. 37). Therefore, it is always necessary to check if convergence has been achieved before one starts to make inferences. A quick (visual) check for convergence can be performed by inspecting the history plots produced by OpenBUGS. Three chains with very different initial values are run simultaneously. In the first chain, the starting values of β_{0_k} (i.e., intercept), β_{1_k} (i.e., prior war), β_{2_k} (i.e., economic development) and β_{3_k} (i.e., population) ($k = 1, 2, \ldots, 55$) are taken from the crude estimates of a simple logit regression model (i.e., assuming constant coefficients). The initial values of all beta’s are set equal to zero in the second chain and, in the last chain, the value of 10 is used to make the three sets of initial values quite dispersed. To save space, only a few history plots are shown in Figure 2.



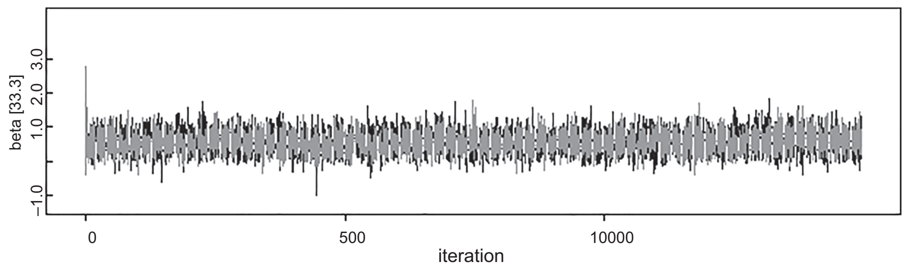
(a) β_{0_k}



(b) β_{1_k}



(c) β_{2_k}



(d) β_{3_k}

Figure 2.
History plots for Beta's at $k = 33$

It can be seen that the three sequences of simulations settle into a similar range very quickly, indicating that convergence has been achieved.

A more rigorous approach to diagnosing convergence is the Brooks-Gelman-Rubin (BGR) diagnostic available in OpenBUGS when multiple chains are generated concurrently. This statistic is constructed based on the intuition that, after convergence, all the chains should basically behave the same way, and variance within the chains is expected to be the same as that across the chains. Therefore, the BGR statistic (noted as R in OpenBUGS), a ratio of the pooled chain variance to the within chain variance, should approximately equal one in order to indicate convergence. Besides reporting the R statistic (the red line), the BGR diagnostic plot also tracks the normalized width of the central 80% interval of the pooled runs (graphed by the green line) and the normalized average width of the 80% intervals within the individual runs (shown as the blue line). As Brooks and Gelman (1998) stress, one should also be concerned with the stabilization of both the pooled and within interval widths when deciding where convergence has occurred. Figure 3 displays selected BGR plots. (please, note that Figure 3 is presented in black-and-white in order to reduce the file size. The color figure is submitted as a supplementary file). The plots illustrate that R converges to "1.0" before 2000 iterations while it takes a bit longer for the pooled and within interval widths to stabilize. Thus, a conservative burn-in of 5000 iterations is used for each chain. With an update to 10,000 iterations, using three chains, this study obtains a total of 30,000 iterations for subsequent analysis.

6. Model selection

In order to choose the model specification that fits the data better, several other model specifications are also considered; these include using a time-invariant intercept, leaving out country-specific effects, or incorporating additional explanatory variables. A convenient model comparison tool built into OpenBUGS is the deviance information criterion (DIC), which has been recently popularized for Bayesian model selection due to its computational ease. Being an adaptation of the Akaike information criterion for Bayesian models incorporating prior information, DIC consists of two components: the posterior mean of the

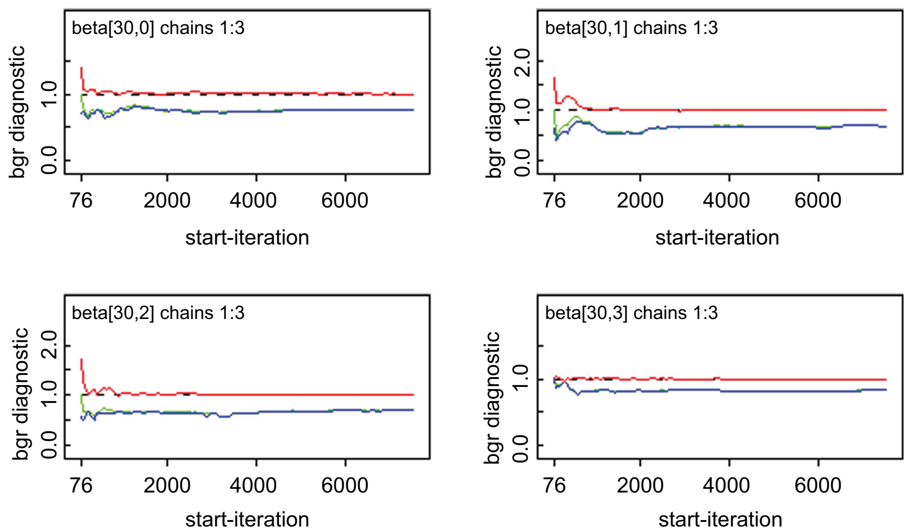


Figure 3.
Brooks-Gelman-Rubin (BGR) plots: β_{0_k} through β_{3_k} at $k = 30$

deviance (Dbar) as a measure of fit and an assessment pD of the 'effective number of parameters' as a measure of complexity (Spiegelhalter *et al.*, 2002; Lunn *et al.*, 2009).

By comparing the DIC statistics (see Appendix) for the various models explored, it follows that the current model has the smallest DIC value and thus is a preferable model to use for addressing the research question posed in this study.

7. Structural changes or nil?

As this study investigates the time constancy of the civil war model, the main interest lies in the variation among the time-indexed coefficients. One or more statistically significant coefficient shifts should provide support for the argument that the mechanism underlying civil war evolved after Second World War. In terms of policy implications, this should help policymakers identify factors which are more relevant to contemporary internal conflicts and thereby devise suitable policies geared toward defusing civil violence-prone situations at home.

7.1 Visual inspection

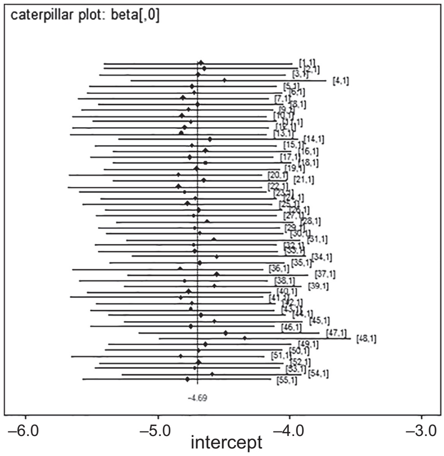
A caterpillar plot is one of the graphical comparison facilities that OpenBUGS offers; it can serve as a shortcut to our goal of detecting time-varying regression coefficients. A caterpillar plot illustrates a side-by-side comparison of the posterior distributions of each element in a parameter vector. Each posterior distribution is summarized by a horizontal line representing the 95% credible interval and a dot marking the posterior mean. The default baseline (i.e., the vertical line in the middle of each plot) is the global mean of the posterior means. Due to its greater simplicity, a caterpillar plot is typically preferred over a boxplot when the number of distributions to be compared is large.

By inspecting the caterpillar plots in Figure 4, this study found that the posterior means of coefficients appear to vary appreciably in certain years and that not all explanatory variables demonstrate an alteration in their influence at the same time. To be specific, in the caterpillar plot for coefficient vector beta[,0] (i.e., the posterior distributions of time-indexed intercepts), the posterior means of the 4th, 47th and 48th years (corresponding to the years 1948, 1991 and 1992, respectively) stand out relative to the global mean represented in the plot by the vertical line. Horizontal lines with [] in Figure 4 represent years in order; for example, [1,1] means the first year for β_{0_k} (i.e., intercept). Among the yearly coefficients pertaining to previous wars (denoted as vector beta[,1]), the posterior means for the 47th and 48th years look somewhat different from the rest years. As to the parameters for economic development (specified as vector beta[,2]), the 4th and 25th years appear to have a posterior mean which does not conform as well with the other years. Regarding the coefficients for population (referred to as vector beta[,3]), the posterior means for the 4th and 6th years seem distinctive.

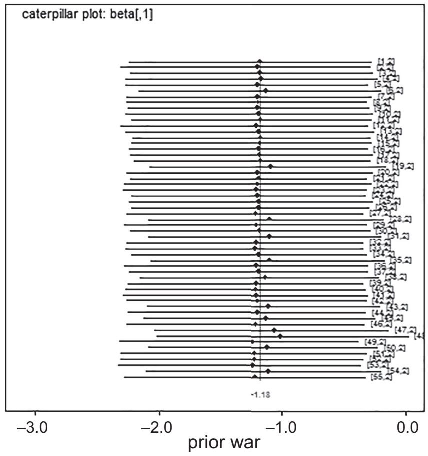
It should be noted that the caterpillar plots only serve as a rough guide. In order to encompass the 95% interval of all posterior distributions under comparison, the scale of the plots is adjusted accordingly, thus rendering the discrepancies in the posterior means more noticeable in some cases. Furthermore, we notice that in each caterpillar plot, the horizontal lines span largely overlapping ranges, covering, in particular, one another's posterior mean. This indicates that the shifts in posterior means might not be sufficiently substantial to justify a conclusion that structural breaks have occurred.

7.2 Hypothesis testing

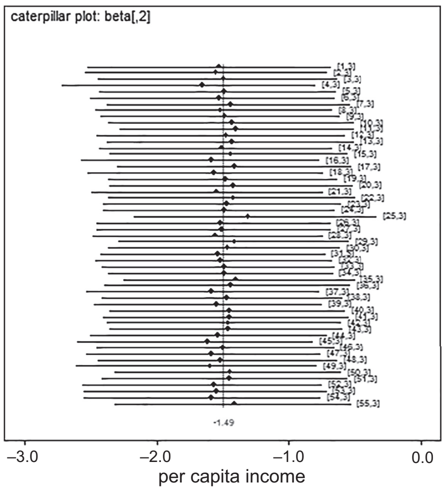
Although the caterpillar plots are indicative of possible changes in the size of regression coefficients, they fall short of meeting the standard of statistical rigor. This section introduces



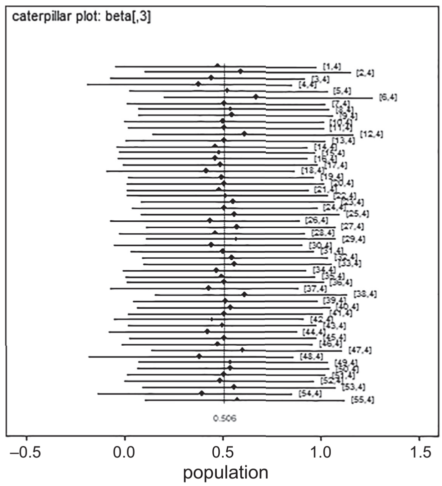
(a) β_{0_k}



(b) β_{1_k}



(c) β_{2_k}



(d) β_{3_k}

Figure 4.
Caterpillar plots

four formal tests to check the presence of any changepoint in the effects of conflict-inducing factors that are scrutinized in this paper; these tests are as follows:

(1) Comparison tests with respect to the difference between a given coefficient and its global mean.

The rationale here is that if a structural break occurs, then one or more regression coefficients associated with that time period should divert from the average level of the regression coefficient(s) over the whole study period (i.e., the global mean). For this reason, the following hypothesis is posited:

H1. If no regression coefficient is meaningfully different from its global mean, no structural break exists.

This hypothesis can be expressed in mathematical form as follows:

$$gd\_\beta_{i_k} = gm\_\beta_i - \beta_{i_k} = 0 \quad \forall i \text{ and } k,$$

where $i = 0, 1, 2, 3$, denoting the coefficient vector and as before, k indexes the 55 time periods under study.

A Monte Carlo approach is adopted for the hypothesis testing. Replying on the 30,000 simulations that OpenBUGS generates for each β_{i_k}, we can easily obtain 30,000 random values for their global means by averaging across the 55 time periods [4]. Subsequently, we subtract the 30,000 iterations for a given β_{i_k} from their corresponding global means and thereby acquire 30,000 samples of the difference between the regression coefficient and its global mean, with which we can perform a comparison test with respect to the hypothesis. We may take advantage of the density plot that OpenBUGS is able to generate, based on the aforementioned 30,000 sampled differences and check where the value of zero falls in the density distribution. If the value zero occurs in a very likely region, it indicates that there is not sufficient evidence to reject the null hypothesis of no structural break. Equivalently, we may use the 95% interval that OpenBUGS calculates by default for the variable $gd\_\ \beta_{i_k}$ using the 30,000-sample and check whether or not it contains the value zero. Both the 95% interval and density plots lead to the same conclusion, namely, that the observed shifts in the posterior means of regression coefficients are not statistically significant to affirm any structural break. To save space, only a few density plots are shown in Figure 5 for illustration.

To alleviate the concern that a sharp shift in a regression coefficient might bias the global mean toward itself and thus make its variation from the global mean less appreciable, we also calculated global means by excluding the regression coefficient currently in question. A reexamination of the density plots using this second type of global means still cannot find enough evidence to conclude that any structural change occurred either in the regression intercept or in the coefficients for the explanatory variables, i.e., prior war, economic development and population. Selected density plots are presented in Figure 6. In each plot, the density distribution is more or less centered around the value zero, thus signaling failure to reject the null hypothesis that the regression coefficients do not exhibit any structural change.

(2) Comparison of posterior distributions using possible changepoint years identified from caterpillar plots

In situations where earlier and later structural changes appear in the opposite direction, but where their magnitude is about the same, a comparison with the global mean may not provide much help in detecting any irregularities. To circumvent such possibilities, this study considers another test that serves as a complement to the previous tests in spotting potential structural breaks; in this case, we follow up the caterpillar plots with hypothesis testing wherever a notable variation in the posterior means is observed earlier in the graphic diagnosis. In particular, we compare the sequence of simulations of a coefficient for a specific year to that of the preceding year. If a 95% interval for the difference between the two sequences does not include the value zero, it is plausible that a structural break has occurred between these two years. For instance, regarding the impact of economic development, we suspect that based on their locations in the caterpillar plot, a structural break may occur between the 4th and 5th years, and therefore we are interested in knowing if the hypothesis that $\beta_{2_4} = \beta_{2_5}$ (or equivalently, $d\_\beta_{2_{4,5}} = \beta_{2_4} - \beta_{2_5} = 0$) holds. Given the 30,000 simulated values of β_{2_4} and β_{2_5} at hand and then subtracting the latter from the former will render us a random sample of 30,000 for the newly created variable $d\_\beta_{2_{4,5}}$. Similarly, we can apply a comparison test to this simulated sample by either checking the 95% interval of the sample

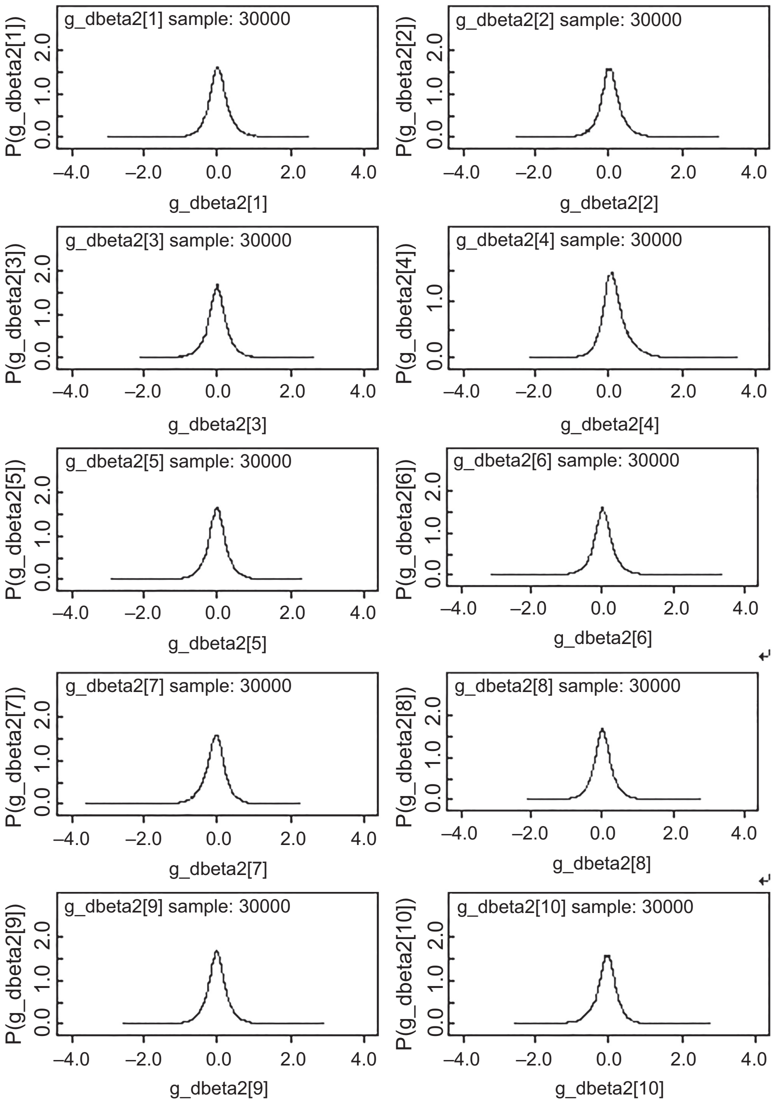


Figure 5.
Density plots (selected time periods, $k = 1, 2, \ldots, 10$): Difference between coefficients on economic development and their (default) global mean

or plotting its density distribution, to assess if a structural change takes place with respect to the impact of income on the incidence of civil war in the period between these years.

According to the caterpillar plots drawn earlier, possible changepoint years are the 4th, 6th, 25th, 47th and 48th. Hence, simulations of the coefficients for these years are compared with their previous year's values, respectively, and the density distributions of the differences between those sequences are reported in Figure 7.

In the same manner, both the 95% intervals (see Appendix) and the density distributions of the differences in the coefficients for the period between those specified years provide no support for there being a structural break in the regression model.

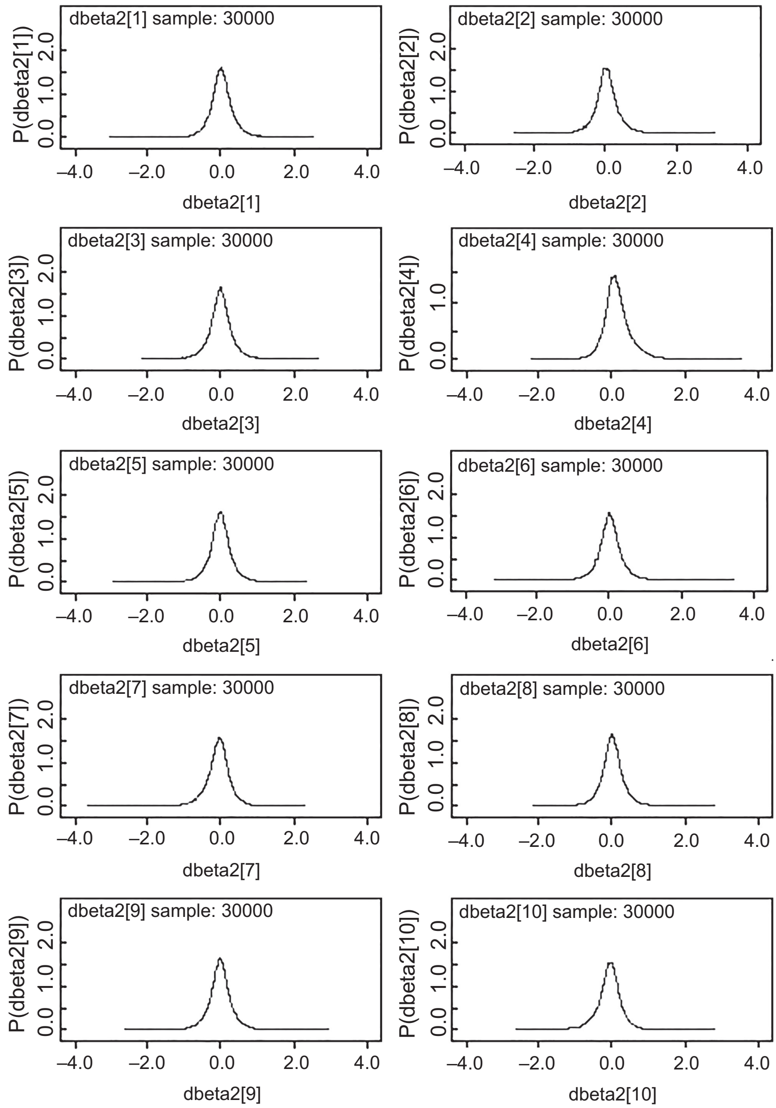
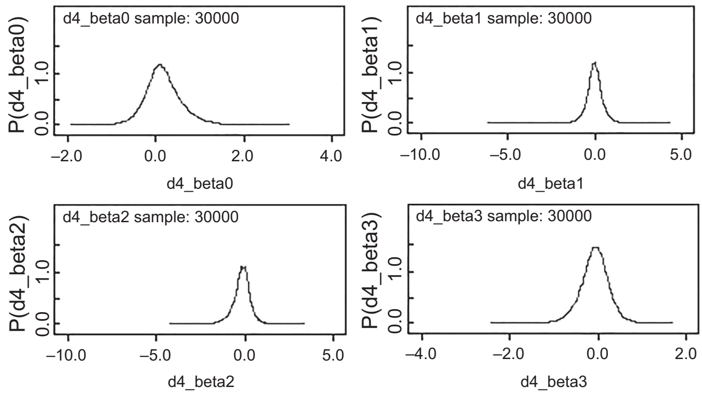


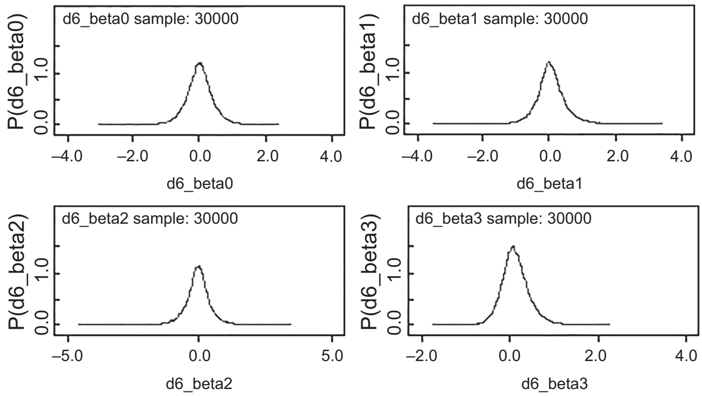
Figure 6.
Density plots (selected time periods, $k = 1, 2, \ldots, 10$): Difference between Coefficients on economic development and their (modified) global mean

(3) An overall significance test

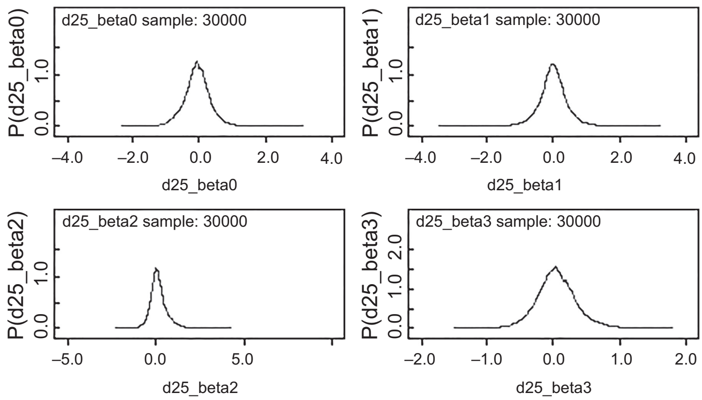
So far, we have applied comparison tests to individual regression coefficients and found that, individually, each covariate parameter tends to be quite stable over time. Next, we performed an overall significance test (as a final test) to check if the logit regression changepoint model, as a whole, works better than a traditional logit regression model in terms of fitting the civil war data. To this end, we again resorted to the DIC statistics as the comparison criterion.



(a) β_{0_k} through β_{3_k} at $k = 4$



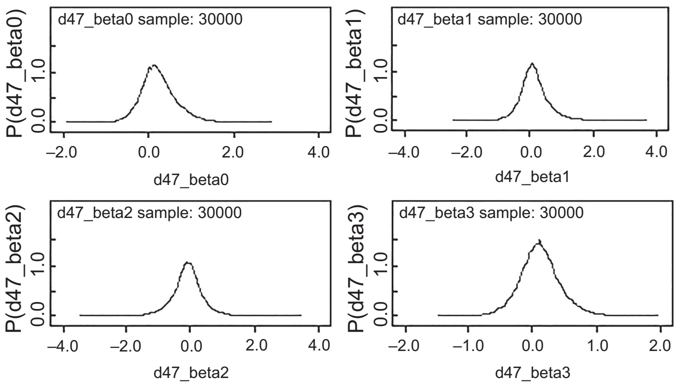
(b) β_{0_k} through β_{3_k} at $k = 6$



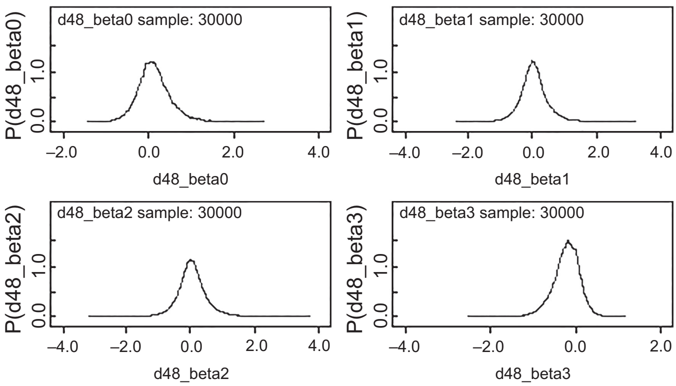
(c) β_{0_k} through β_{3_k} at $k = 25$

Figure 7.
Density plots

(*continued*)



(d) β_{0_k} through β_{3_k} at $k = 47$



(e) β_{0_k} through β_{3_k} at $k = 48$

Figure 7.

The comparison model is defined in a similar fashion, except that now all covariate parameters are assumed to be constant over time. Specially,

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1_i} + \beta_2 x_{2_i} + \beta_3 x_{3_i} + b_i, \tag{2}$$

where $i = 1, 2, \ldots, 156$, denoting the 156 countries sampled and b_i representing the country-specific effects. Running this constant parameter model in OpenBUGS, following the same procedure detailed earlier in this study, we obtained a DIC value which is the same as the one reported for the changepoint model (models 1 and 6 in Appendix). This further confirms that there is no structural change in the civil war model.

Our analysis, either by means of graphic diagnostic or formal test, produces consistent results, indicating that the relationship between civil war and its economically relevant determinants has been quite stable over time, particularly during the period, 1945–1999. This finding is consistent with what Fearon and Laitin report in their study. Economic development, population and prior war all have a significant bearing on the outbreak of civil conflict. As explained in Fearon and Laintin's study, a higher level of economic development seems to dampen the incentive for minority groups to initiate civil strife, either because an affluent citizenry may harbor less grievances or because a strong state can carry out effective counterinsurgency operations. Countries with a denser population are more likely to fall into internal conflict. It also appears that the incidence of a civil war in a previous year deters the occurrence of a new one.

8. Conclusion

Since changepoint analysis is instrumental in determining whether important changes have taken place in the mechanism of politico-economic phenomena, several existing studies across disciplines have striven to develop various types of structural break models. The recent works by Spirling (2007) are notable because their models help test the existence of changepoints in a "political" phenomenon and their effects. However, because their models rely exclusively on a series of time ordered data within a country, they are unsuitable for addressing research questions that are related to cross-sectional, time-series phenomena. This study has filled the gap by introducing a practical approach for analyzing structural break problems in cross-sectional, time-series data. To be specific, the complexity of structural break models makes numerical integration methods inevitable and thus Markov chain Monte Carlo (MCMC) becomes an more appropriate method for addressing this type of question. However, programming a MCMC analysis of structural break models from scratch poses a real challenge for applied researchers. This study has presented a user-friendly approach to implement complicated structural break models by utilizing the computational advantage of OpenBUGS. Compared to previous structural break techniques, this approach is more flexible in that it better handle those cases where all the parameters are not required to shift at the same time, where transitions between regimes may go back and forth, and where cross-sectional, time-series data are applicable. In addition, given how model building is conducted in OpenBUGS, model modification can be easily executed.

Based on graphical diagnosis and hypothesis testing with the assistance of the computational facilities built in OpenBUGS, this study proposes a new Bayesian changepoint logit model to reexamine the conventional wisdom that the mechanism underlying the onset of civil war has changed in the post-Cold War era. Our empirical results indicate that during the time period 1945–1999, economic development, population and prior civil war incidence have all affected civil conflict in a significant but unvarying manner. This echoes Fearon and Laitin's (2003) finding that the mechanism of civil war has remained stable since 1945 and that the impact of civil conflict-inducing factors did not shift in response to the new, post-Cold War international system as has been speculated. Identifying the causal factors of civil wars, especially detecting the presence or absence of structural change in the causal link between civil war and its determinants in the contemporary world, is of great importance to policymakers. If appropriate policies addressing the most relevant conflict-inducing factors are taken into account, potential civil conflicts can be defused and prevented at an early stage. In this sense, the approach presented in this study is uniquely meaningful in that it is capable of differentiating individual changes in the effect of covariates that do not occur around the same time, a type of parameter shift that other changepoint models might not have the flexibility to recognize and address. This capability of tracking the time-varying movements in the parameters of individual covariates can help policymakers focus more on those variables of interest and, thus, use them to make timely policy adjustments.

Notes

1. OpenBUGS is a free computer software program for the Bayesian analysis of complex statistical models using Markov Chain Monte Carlo (MCMC) methods. It runs under Windows and Linux, as well as from inside the *R* statistical package.

2. Bai and Perron (1998) consider the case of a partial structural change model where not all parameters are subject to shifts.
3. Fearon and Laitin state that "if many post-1945 civil wars have been "ethnic" or "nationalist" as these terms are usually understood, then even more have been fought as *insurgencies*" (p. 79).
4. This is the default of global mean calculated by OpenBUGS.

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Further reading

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Appendix

The Appendix file is available online for this article.

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