One of the main empirical conclusions of the political business cycle literature is that economic growth and employment in the United States tend to fall after the election of a Republican administration, and increase following Democratic victory. Because Republican administrations also exhibit lower interest rates and inflation than Democrats, it has been argued that their constituents favor lower inflation at the expense of lower growth and employment, while Democrats are willing to bear increased inflation in exchange for lower unemployment. This article examines the joint behavior of output growth, unemployment, interest rates and inflation, and provides evidence challenging the notion that this is a static choice. In the context of a dynamic macroeconomic system that also involves election outcomes, we find that long-run Republican outcomes dominate Democratic ones on all margins (high growth and employment, low interest and inflation) – growth is shown to reverse relatively quickly, employment adjusts more slowly, and the short-run differences in interest and inflation increase dramatically in the long-run. This finding cautions against static interpretations of partisan differences, and suggests that these differences should be viewed in an intertemporal setting in which the two parties choose different ways of balancing short-run costs and benefits with those in the long run. For the electoral part of the model, we find suggestive evidence that both economic and non-economic variables (e.g. growth, war fatalities) are relevant determinants of vote shares and can improve predictions relative to conditioning solely on economic outcomes such as growth and inflation.

Keywords: Bayesian estimation; economic growth; election outcome; inflation; interest rate; Markov chain Monte Carlo (MCMC); partisan cycle; political business cycle; steady state; unemployment.

1 Introduction

Government policies have strong and lasting effects on the economy and can influence the behavior of macroeconomic aggregates in both the short and the long run. Yet, in democratic societies, governments are held accountable for their actions through the electoral process, so that the state of the economy can in turn affect election outcomes and future economic policies. Because of the
importance of these effects, it is not surprising that a flourishing empirical literature on political business cycles has devoted much effort to examining the relationship between politics and economics. This article revisits the study of political business cycles using a joint dynamic system of macroeconomic and electoral outcomes. Our methodology deals with the drawbacks of single-equation estimation, allows us to formally take advantage of non-sample information, and yields important new results revealing key intertemporal trade-offs in partisan outcomes that have not been documented in earlier work.

The existing empirical literature on the interactions between economic and political outcomes in the post-war United States has recorded a number of interesting regularities in the data. Two important findings are that output growth and employment are higher under Democrats than under Republicans, and that aggregate economic outcomes, most noticeably output growth, tend to influence the incumbent’s vote share and probability of re-election. In early work, Hibbs (1977, 1987) argues that the two parties prefer different trade-offs between unemployment and inflation because of differences in constituencies and ideologies, and hence lead the economy to different points on the Phillips curve. His estimates suggest that unemployment is approximately 2 percentage points higher and inflation declines by a similar amount when Republicans control the White House relative to a Democratic administration. Subsequent empirical results (Alesina and Sachs 1988; Alesina 1988; Alesina et al. 1993) have illustrated economic outcomes tend to diverge in the first two years of a President’s term, but converge in the second half of the term. This result is supported by Verstuyk (2004), who finds that in the first two years after an election gross domestic product (GDP) growth can be 3.65 percentage points higher under Democrats than under Republicans; his estimates suggest that the difference dwindles to 0.4 percentage points in the last two years of the administration’s mandate. A study of financial markets by Santa-Clara and Valkanov (2003) reveals larger excess returns in the stock market during Democratic presidential terms and the finding appears to be robust to conditioning on macroeconomic data and election dates.

While political ideology is one factor affecting a government’s economic policy, Nordhaus (1975) notes that incumbent governments also have an incentive to manipulate policy opportunistically just before elections to improve their odds of reelection; historical evidence supporting this view is provided in Abrams (2006) in a study of the Nixon tapes. Similarly, economic agents also take elections into account: Garfinkel and Glazer (1994) find that in the face of electoral uncertainty,
economic agents respond by delaying action until that uncertainty has been resolved – one of their empirical findings is that long-term labor contracts are clustered in periods after elections. Since the early work of Kramer (1971) which argued that economic outcomes will affect elections, a number of quantitative models (e.g. Fair 1978, 1996; Alesina et al. 1993; Abrams and Butkiewicz 1995; Verstyuk 2004; Hibbs 2007) have evaluated the empirical relevance of various determinants of electoral behavior. Detailed reviews of the literature on the interactions between economics and politics and additional discussion of the causes and effects of political business cycles is offered in Alesina, Roubini, and Cohen (1997), Persson and Tabellini (2000), and Drazen (2000a, 2000b). A careful recent study of the empirical interaction between politics and economic outcomes is given in Verstyuk (2004) using reduced form models; a structural model of economic development conditional on political regimes is analyzed in Milani (2007), while Jones, Kim, and Startz (2007) study political regimes using a Markov switching model.

Throughout this paper we focus on the joint modelling and simultaneous estimation of a dynamic system involving Presidential election outcomes and a number of macroeconomic variables. Data deficiencies and econometric complexity have mainly restricted attention to single equation models that consider the impact of elections on variables such as unemployment, inflation, or output growth one at a time. But the dangers of single-equation modelling can not be underestimated – such models are not models of the economy as a whole and are ineffective at accounting for the dynamic interaction and feedback effects that occur as the economy evolves. For instance, macroeconomic theory suggests that increased unemployment would put downward pressure on wages and inflation, while lower interest rates would spur investment and economic growth; interactions and feedback effects such as these should, therefore, be an essential part of the empirical model but are largely ignored in single equation models despite their importance. We approach this and other related issues by building a Bayesian dynamic model in which all variables—the macroeconomic and political outcomes—are allowed to interact fully and are determined and estimated jointly. The econometric methodology we employ allows us to address several important problems in ways that distinguish our approach from earlier work. In addition to overcoming the empirical flaws of single-equation estimation, the econometric approach allows us to take advantage of non-sample information in order to deal with the problem of micronumerosity, or small samples (there have been only 15 presidential elections in the post-war U.S. history). The problem of micronumerosity
is unlikely to be resolved anytime soon, as it will take a lifetime to even double the sample on electoral outcomes. In order to be able to draw inferences about political processes and deal with micronumerosity, we approach the problem within a Bayesian inferential framework by constructing informative proper priors. Such priors help the analysis in multiple ways – they improve parameter identification, embody and borrow strength from theoretical and historical considerations, yield finite sample inferences, and allow finite sample probabilistic comparisons among a number of alternative nested and non-nested models through formal methods such as marginal likelihoods and Bayes factors.

The key finding of this paper is that the initial post-election partisan equilibria are transient and that the early Democratic booms and Republican downturns are reversed as the economy evolves. Eventual Republican macroeconomic equilibria dominate the Democratic ones on all margins, yielding higher growth and employment and lower interest and inflation. Our results reveal that macroeconomic interactions indeed have large long-term effects in addition to the short-run business cycle effects, and that taking a system approach to modelling the macroeconomy, rather than estimating single-variable equations one at a time, is extremely important in capturing those economic interactions. Our results are consistent with the possibility that at the crux of political business cycles lies an important intertemporal trade-off where Democrats pursue “instant gratification” where higher growth in the short-run comes at the cost of lower long-run growth and higher inflation in both the short- and long-run, whereas Republican policies achieve long-term benefits (high growth, price stability) but come at the cost of a sizeable short-run economic slowdown.

For the electoral part of the system, we compare several competing model specifications that deal with the problem of variable selection in order to produce a parsimonious but theoretically adequate specification. Our results reveal that GDP growth is an empirically relevant determinant of relative vote shares. However, we also find suggestive evidence that a model that includes non-economic covariates such as war fatalities (Hibbs 2000, 2007) in addition to GDP growth, can improve predictions relative to conditioning solely on economic outcomes such as growth and inflation.

The rest of the paper is organized as follows. In section 2 we present the empirical model and the Bayesian estimation method used in our analysis. Section 3 describes the data and the approach we take to obtain proper informative priors. In Section 4 we present our main results,
while Section 5 contains concluding remarks.

2 Methodological Framework

2.1 The Statistical Model

In this section we present the statistical framework used to model the joint evolution of real output growth $g_t$, unemployment $u_t$, nominal interest rates $i_t$, and inflation $\pi_t$, which are included in a vector of macroeconomic data $y_{mt} = (g_t, u_t, i_t, \pi_t)'$, and a scalar political outcome variable $y_{pt}$, which is a transformation of election vote shares that will be discussed shortly (all data will be fully summarized in Section 3). Only the vector $y_{mt}$ is observed between elections; in contrast, election periods provide observations on the joint outcome $y_t = (y_{mt}', y_{pt})'$. The time series evolution of $y_{mt}$ is modelled through the vector autoregressive (VAR) system

$$y_{mt} = \mu_m + \sum_{j=1}^{p} F_{mj} y_{t-j} + G_m z_{t-1} + \varepsilon_{mt}, \quad (t = 1, 2, ..., T), \tag{1}$$

where $\mu_m$ is a vector of intercepts, $F_{mj}$ ($j = 1, ..., p$) and $G_m$ are matrices of coefficients, and $p$ represents the number of lags. In the above, dependence on the political composition of the government is modelled through the dummy variable $z_{t-1}$ indicating whether the President is a Republican ($z_{t-1} = 1$) or a Democrat ($z_{t-1} = 0$). VAR models have become the workhorse in much of empirical macroeconomics since the work of Sims (1980a, 1980b), although these models have not generally been applied in the political business cycle literature (an important recent exception is given in Faust and Irons 1999, who studied the role of monetary policy in cyclical fluctuations).

There are several benefits of estimating a system as opposed to a number of separate equations. First, it can be shown by recursive substitution for the individual series that even a low-order VAR system, such as VAR(1), can produce autoregressive moving average (ARMA) dynamics that are capable of capturing rather sophisticated oscillatory and hump-shaped dynamics that are important in this setting but can not be produced by simple single-equation autoregressive models. Two important exceptions in the single-equation literature are given in Alesina et al. (1993) and Verstuyk (2004) who estimated single-equation economic models with ARMA dynamics. Second, a system of equations explicitly accounts for interactions between the macroeconomic variables unlike simpler models which most often use only own lags and ignore feedback effects, in contradiction with macroeconomic theory. Finally, allowing for correlation in the errors has the usual important

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5
implications for statistical efficiency. Working with a reduced form VAR is convenient in our setting because all results that will be presented in the remainder of the paper—e.g. evaluating the steady state of (1) or the evolution path through which the economy gets there—are available in this framework without making additional structural identification assumptions. In addition, the modelling does not restrict the interactions between economics and politics, and allows both fiscal and monetary channels of policy transmission. This is important given the recent results in Faust and Irons (1999) and Drazen (2000b), who have argued that monetary policy may play a somewhat passive role, largely accommodating fiscal policy impulses; however, we do not want the model to disregard the historical record offered in Abrams (2006) which offers direct evidence of opportunistic political behavior aimed at affecting monetary policy.

For the purposes of estimation, equation (1) will be written in the form of a seemingly unrelated regression (SUR) model (Zellner 1962) as

\[ y_{mt} = X_{mt}\beta_m + \varepsilon_{mt}, \]  

where \( X_{mt} \) is given by

\[
\begin{pmatrix}
(1, y'_{mt-1}, \ldots, y'_{mt-p}, z_t) \\
(1, y'_{mt-1}, \ldots, y'_{mt-p}, z_t) \\
\vdots \\
(1, y'_{mt-1}, \ldots, y'_{mt-p}, z_t)
\end{pmatrix}
\]

and \( \beta_m \) is a vector containing the corresponding parameters from \( \mu_m, F_{mj} \ (j = 1, \ldots, p) \) and \( G \) ordered equation by equation.

Unlike the macroeconomic outcomes \( y_{mt} \) which are available every period, our political outcome \( y_{pt} \) is only observed once every 16 quarters – presidential elections in the U.S. are generally scheduled to take place on the Tuesday after the first Monday in November in even-numbered years every four years, and duty generally commences in January of the following year. To model the political outcomes in election periods, the system in (2) is augmented with an equation for the election result that is given by

\[ y_{pt} = x'_{pt}\beta_p + \nu_t, \]

where \( x_{pt} \) is a covariate vector that contains measures of economic performance and indicators of the political status quo. The particular choice of covariates is guided by Fair (1996) and Hibbs (2007) and is further discussed in Section 4. In our application, the dependent variable \( y_{pt} \) is a
transformation of the electoral vote share for the Republican presidential candidate. The transformation is needed in models of relative shares in order to produce a coherent probabilistic model due to the fact that share data are necessarily restricted between 0 and 1. For this reason, we use \( y_{pt} = \Phi^{-1}(\text{voteshare}_t) \) with \( \Phi^{-1}(\cdot) \) being the inverse of the standard normal cdf applied to the two-party vote share for the Republican candidate, so that \( y_{pt} \) is now unrestricted. Other transformations, most notably the logit transformation \( \logit(s) \equiv \log(s/(1-s)) \) are also frequently applied in the analysis of share data, but mostly result in re-scaling of the parameters without substantially affecting the marginal effects. The transformation is essential for producing a theoretically coherent model in which the vote share is guaranteed to be in the range \((0,1)\), even though in our application the political outcomes are focused in a much tighter range around 0.5 where the probit and logit link functions are locally linear and parameter interpretation is not complicated very much.

While the model in (4) adheres to the existing literature on voter behavior (Fair 1996; Alesina et al. 1993, Hibbs 2007) and studies the two-party vote shares as in earlier studies, we note that in principle equation (4) could be specified as a probit model for the winner in an election, leading to the QualVAR model in Dueker (2005). We briefly diverge to note some benefits and drawbacks resulting from either choice and to emphasize that the two models are complementary. One benefit that makes the election vote share a preferable measure of political outcomes is that it is continuous, rather than binary, and the scarcity of observations on election outcomes makes identification and estimation of binary data models less feasible. Moreover, the vote share measure provides more information about the political sentiment driving the election outcome as opposed to the binary variable that simply tells us who won, but not by how much. A drawback of the vote share data, however, that one must be mindful of when interpreting the results, is that vote shares do not perfectly correspond to eventual victory because of peculiarities of the U.S. electoral college. As a case in point, George W. Bush lost the popular vote to Al Gore in 2000, but nonetheless went on to win the Presidency. These considerations do not invalidate one model or the other as they deal with different aspects of the political process, but do imply that care is needed in distinguishing the two: the continuous data on vote shares measures voter sentiment, whereas the binary data model is a predictive model for election outcomes.

To summarize these considerations, in periods without elections, our model consists of equation (2) alone, while in quarters when elections are held, we observe the full system for \( y_t = (y_{mt}', y_{pt}')' \)
that combines (2) and (4) and is written as

\[ y_t = X_t \beta + \varepsilon_t \]  

(5)

where \( X_t \) is a covariate matrix in SUR form given by

\[ X_t = \begin{pmatrix} X_{mt} & 0 \\ 0 & x_{pt}' \end{pmatrix} \]

with \( X_{mt}, x_{pt}, \) and \( \beta = (\beta'_m, \beta'_p)' \) as defined in (2), (3) and (4) and \( \varepsilon_t = (\varepsilon_{mt}', \nu_t)' \). To permit the disturbances underlying the political outcome variable to be correlated with those of the economic performance component, as is typical in SUR models, the individual equations are united through a correlated error process of the form

\[ \varepsilon_t \sim N \left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix} \right) \equiv N(0, \Sigma). \]  

(6)

Allowing for unrestricted correlation is important for both practical and theoretical reasons. For example, unobserved exogenous shocks, such as changes in the foreign investment climate, international security, or energy and commodity prices, might simultaneously impact political attitudes as well as the macroeconomy. From an econometric point of view, the usual efficiency and finite sample arguments apply: while the expected values of the parameters in repeated samples may be the same whether or not the covariance is accounted for, the finite sample estimates and their dispersion will generally depend on that covariance, so that accounting for it is statistically desirable.

2.2 Estimation

In this section, we address the special estimation difficulties that emerge as a result of the unequal frequencies with which economic and electoral outcomes are observed. The unequal frequencies produce an unbalanced sample where the parameters are identified from different sub-samples depending on what data are observed. This induces a difficulty with estimating the covariance between economic and political outcomes in the model. To deal with this problem, we adapt estimation techniques from the Bayesian literature on incidental truncation models (Chib, Greenberg and Jeliazkov 2009), which helps us overcome the estimation difficulties in our context.

Let \( T_1 \) be the subsample of \( T_1 \) non-election quarters and \( T_2 \) be the subsample of \( T_2 \) election quarters. The likelihood function is given by the product

\[ f(y|\beta, \Sigma) = \left\{ \prod_{t \in T_1} f(y_{mt}|\beta_m, \Sigma_{11}) \right\} \left\{ \prod_{t \in T_2} f(y_t|\beta, \Sigma) \right\}, \]
where
\[
\begin{align*}
  f(y_{mt}|\beta_m, \Sigma_{11}) & \propto |\Sigma_{11}|^{-1/2} \exp \left( -\frac{1}{2} (y_{mt} - X_{mt}\beta_m)' \Sigma_{11}^{-1} (y_{mt} - X_{mt}\beta_m) \right), \\
  f(y_t|\beta, \Sigma) & \propto |\Sigma|^{-1/2} \exp \left( -\frac{1}{2} (y_t - X_t\beta)' \Sigma^{-1} (y_t - X_t\beta) \right).
\end{align*}
\]

We note that the elements of \( \beta \) and \( \Sigma \) are identified through different samples – \( \beta_m \) and \( \Sigma_{11} \) enter the likelihood function in both \( T_1 \) and \( T_2 \), while \( \beta_p, \Sigma_{12}, \) and \( \Sigma_{22} \) only enter the likelihood through the observations in \( T_2 \). For this reason, the Markov chain Monte Carlo (MCMC) estimation algorithm does not follow the usual form for SUR models that has been discussed, for example, in Chib and Greenberg (1995). However, the unbalanced structure of the data in our model is reminiscent to that of an incidental truncation model, where some outcomes are observed for some part of the sample and are not observed otherwise, so that different sets of parameters are updated in different subsamples. We rely on this observation in our empirical strategy, which makes it possible to apply the MCMC simulators presented in Chib, Greenberg, and Jeliazkov (2009) to obtain a random sample from the posterior distribution and learn about the parameters of interest. The procedure overcomes the difficulties posed by unbalanced data sets and still allows posterior simulation from known normal and inverse Wishart distributions. Following a burn-in of 5000 MCMC iterations, our main MCMC run includes 30000 MCMC draws that are used to form posterior inferences. In particular, given a truncated normal prior for \( \beta \), i.e. \( \beta \sim T\mathcal{N}_{\{\beta \in S\}}(b_0, B_0) \) so that \( \beta \) is restricted to the region of stationarity \( S \) for which the system in (1) is non-explosive, and an inverse Wishart prior for \( \Sigma \), i.e. \( \Sigma \sim \mathcal{IW}(\nu_0, R_0) \), we obtain a sample of draws for \( \beta \) and \( \Sigma \) using a Gibbs sampler which sequentially draws from full conditional distributions by repeating the following steps.

**Algorithm 1 MCMC Estimation Algorithm**

1. Sample \( \beta|y, \Sigma \sim T\mathcal{N}_{\{\beta \in S\}}(b, B) \) as follows

   (a) Draw \( \beta|y, \Sigma \sim \mathcal{N}(b, B) \), where

   \[
   \begin{align*}
   B &= \left( B_0^{-1} + \sum_{t \in T_1} JX_{mt}'\Sigma_{11}^{-1}X_{mt}J' + \sum_{t \in T_2} X_t'\Sigma^{-1}X_t \right) \\
   b &= B \left( B_0^{-1}b_0 + \sum_{t \in T_1} JX_{mt}'\Sigma_{11}^{-1}y_{mt} + \sum_{t \in T_2} X_t'\Sigma^{-1}y_t \right)
   \end{align*}
   \]
and $J = [I\ 0]$ is a matrix such that $J\beta = \beta_m$.

(b) Accept the draw of $\beta$ if $\beta \in S$ and reject it otherwise, thus ensuring that the posterior sample of MCMC draws satisfies stationarity. If the proposed draw of $\beta$ is rejected, the last draw repeated.

2. Sample $\Sigma|y, \beta$ in a one-block, three-step procedure by first drawing $\Sigma_{11}$, $\Sigma_{22.1} = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}$, and $\Sigma_{11}^{-1}\Sigma_{12}$, and then reconstructing $\Sigma$ from these quantities

(a) $\Sigma_{11} \sim IW(\nu_0 + T_1 + T_2 - 1, Q_{11})$

(b) $\Sigma_{22.1} \sim IW(\nu_0 + T_2, Q_{22.1})$, where $\Sigma_{22.1} = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}$

(c) $\Sigma_{11}^{-1}\Sigma_{12} \sim \mathcal{N}(Q_{11}^{-1}Q_{12}, \Sigma_{22.1} \otimes Q_{11}^{-1})$, where

$$Q_{11} = R_{11} + \sum_{t \in T_1} (y_{mt} - X_{mt}\beta_m)(y_{mt} - X_{mt}\beta_m)'$$

$$Q = R_0 + \sum_{t \in T_2} (y_t - X_t\beta)(y_t - X_t\beta)'$$

$Q_{22}, Q_{12}$ are obtained by partitioning $Q$, $R_{11}$ is obtained by partitioning $R_0$, conformably with $\Sigma$,

$$Q = \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{pmatrix}, R = \begin{pmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{pmatrix}$$

and $Q_{22.1} = Q_{22} - Q_{21}Q_{11}^{-1}Q_{12}$. The elements of $\Sigma$ are then reconstructed through the transformations $\Sigma_{12} = \Sigma_{11}(\Sigma_{11}^{-1}\Sigma_{12})$, $\Sigma_{21} = \Sigma_{12}'$, and $\Sigma_{22} = \Sigma_{22.1} + \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12}$.

Before continuing, we make two computational remarks. First, we note that Step 1 of Algorithm 1 involves an independence chain Metropolis-Hastings step in which the target density $\pi$ and proposal density $q$ satisfy $\pi(\beta|y, \Sigma) \propto q(\beta|y, \Sigma) 1\{\beta \in S\}$ (so that $q$ and $\pi$ would be the same if stationarity were not imposed). This turns out to be quite useful for marginal likelihood estimation and model comparison, which will be discussed in the next section. Second, in our VAR(1) empirical application, stationarity and numerical stability are ensured by requiring that the eigenvalues of $F_{m1}$ in (1) are less than 0.99 in absolute value.

2.3 Model Comparison

In addition to estimation, we also use the building blocks of Algorithm 1 to estimate the marginal likelihoods of several competing models for the purpose of determining their posterior model probabilities. For a given model $M_k$ with its model-specific parameter vector $\theta_k$, the marginal likelihood is defined as the integral of the likelihood function $f(y|\theta_k, M_k)$ with respect to the prior density
prior independence the ordinate of the method of Chib and Jeliazkov (2001) for estimating the density ordinates in this setting. By an adjustment of the normalizing constant to account for stationarity, which is trivially obtained as in Step 1 of Algorithm 1 holding the elements of

\[ m(\pi|\beta, \Sigma) = \frac{f(\pi|\beta, \Sigma)}{\pi(\beta)\pi(\Sigma)} \] 

where the first fraction on the right hand side is known as the prior odds and the second as the Bayes factor. The Bayes factor, therefore, determines the degree to which prior beliefs about models \( \mathcal{M}_i \) and \( \mathcal{M}_j \) are affected after seeing the data \( y \). Chib (1995) notes that since the marginal likelihood of a particular model is the normalizing constant of the posterior density, it can be computed through the identity

\[ m(\pi|\beta, \Sigma) = \frac{f(\pi|\beta, \Sigma)\pi(\beta, \Sigma)}{\pi(\beta, \Sigma)} \]

which follows from Bayes’ theorem and holds for any value of the parameter vector \( \pi \) in the support of the posterior distribution. Suppressing the model indicator for notational convenience, and evaluating this expression on the log scale for some specific value \( \pi^* \), where in our context \( \pi^* = (\beta^*, \Sigma^*) \) is evaluated at the posterior mean, we obtain

\[ \ln m(\pi) = \ln f(\pi|\beta, \Sigma) + \ln \pi(\beta^*, \Sigma^*) - \ln \pi(\beta, \Sigma|\pi) \]

The first term on the right-hand side of this expression is directly available as the log-likelihood function of the model evaluated at \( (\beta^*, \Sigma^*) \), however, the prior and posterior ordinates require additional computations. Fortunately, these computations are fairly straightforward and easy to implement because the Metropolis-Hastings step in Algorithm 1 is simply an accept-reject step due to the fact that \( \pi(\beta|\Sigma, \pi) \propto q(\beta|y, \Sigma)I\{\beta \in S\} \). This observation greatly simplifies the application of the method of Chib and Jeliazkov (2001) for estimating the density ordinates in this setting. By prior independence the ordinate \( \pi(\beta^*, \Sigma^*) \) can be decomposed as \( \pi(\beta^*, \Sigma^*) = \pi(\beta^*)\pi(\Sigma^*) \), which is evaluated as \( \pi(\Sigma^*) = f_{\mathcal{W}}(\Sigma^*|\nu_0, \mathbf{R}_0) \), while \( \pi(\beta^*) \), due to the stationarity restrictions on \( \beta \), is given by

\[ \pi(\beta^*) = \frac{\int f_{\mathcal{W}}(\beta|\beta_0, \mathbf{B}_0)}{\int \sum_{g=1}^{G} 1\{\beta^* \in S\}} \]

over \( G \) draws \( \beta \sim \mathcal{N}(\beta_0, \mathbf{B}_0) \). To evaluate the posterior ordinate \( \pi(\beta^*, \Sigma^*|y) \) we use the decomposition \( \pi(\beta^*, \Sigma^*|y) = \pi(\Sigma^*|y)\pi(\beta^*|\Sigma^*, y) \), where \( \pi(\Sigma^*|y) \) is estimated with draws from the main MCMC run and constructed from the components of Step 2 of Algorithm 1, and \( \pi(\beta^*|\Sigma^*, y) = \frac{f_{\mathcal{W}}(\beta^*|\Sigma^*, \mathbf{Y})}{\sum_{g=1}^{G} 1\{\beta^* \in S\}} \), where \( \mathbf{b} \) and \( \mathbf{B} \) in the numerator are computed as in Step 1 of Algorithm 1 holding the elements of \( \Sigma \) fixed at \( \Sigma^* \). The latter ordinate again requires an adjustment of the normalizing constant to account for stationarity, which is trivially obtained
by averaging the indicator function \(1 \{ \beta^{(g)} \in S \} \) over draws \(\beta^{(g)} \sim N(\beta^* | \mathbf{b}, \mathbf{B})\). We note that the normalizing constants of the prior and posterior densities for \(\beta\) is done very efficiently and easily with as many draws as needed to ensure that the resulting estimates are as precise as needed. Finally, we note that in principle the method of Chib and Jeliazkov (2001) can also be applied with the alternative posterior ordinate decomposition \(\pi(\beta^*, \Sigma^* | \mathbf{y}) = \pi(\beta^* | \mathbf{y}) \pi(\Sigma^* | \mathbf{y}, \beta^*)\), but that decomposition would require an additional reduced MCMC run relative to the decomposition used here, and is therefore less computationally attractive.

The methods described above can be used to produce marginal likelihoods and Bayes factors for competing models to determine the strength of evidence in favor of one specification or another. In the case of dynamic models, the methodology is useful in determining the proper lag-length, but in principle it is used to deal with variable selection more broadly. We apply these techniques in Section 4. However, an important ingredient in the computation of marginal likelihoods and Bayes factors is the presence of a proper prior density on the model parameters. We turn to this issue in the next section.

3 Data and Prior Distributions

Our sample includes post-war quarterly macroeconomic data for the U.S. from 1948:Q1 to 2005:Q1. The set of variables includes output growth \(g_t\) measured by log differences of real GDP between two consecutive quarters, average quarterly unemployment rate \(u_t\), inflation \(\pi_t\) measured by the percentage change in the Consumer Price Index between consecutive quarters, and interest rates \(i_t\) measured by the average quarterly secondary market yield on the 3-month Treasury bill (the first three variables are seasonally adjusted). These variables have been widely used in empirical macroeconomics to reflect the general state of the economy. Table 1 shows descriptive statistics for the aforementioned macroeconomic indicators and White House administrations for our sample period.\(^1\)

From Table 1, we see that the average quarterly GDP growth over the sample period is 0.85

Table 1: Descriptive statistics for the data sample (note: macroeconomic variables are in percentage points).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quarterly growth in real GDP</td>
<td>0.85</td>
<td>1.00</td>
<td>-2.76</td>
<td>4.02</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>5.63</td>
<td>1.52</td>
<td>2.60</td>
<td>10.70</td>
</tr>
<tr>
<td>Nominal interest rate</td>
<td>4.81</td>
<td>2.92</td>
<td>0.79</td>
<td>15.05</td>
</tr>
<tr>
<td>Quarterly Inflation</td>
<td>0.92</td>
<td>0.85</td>
<td>-1.24</td>
<td>4.08</td>
</tr>
<tr>
<td>Republican vote share</td>
<td>0.49</td>
<td>0.07</td>
<td>0.38</td>
<td>0.61</td>
</tr>
</tbody>
</table>

percent, which amounts to annual GDP growth of 3.4 percent. A similar computation shows an average annual inflation rate of approximately 3.7 percent. Unemployment and interest rates average at 5.63 and 4.81 percent, respectively. Republicans govern in 129 of the total of 229 quarters in our sample, indicating a fairly balanced distribution of governance during the period. A striking statistic is often cited in the literature to indicate the strength of correlation between electoral and economic cycles – of the 9 Republican terms in the post-1948 sample, 7 included a recession within 2 years of the election (the exceptions are Reagan’s second term and George W. Bush’s second term), while all 6 Democratic administrations in the sample enjoyed growth in the first two years after the election.²

We analyze these data using Bayesian econometric techniques. The Bayesian inferential approach offers several important benefits, but to extend these benefits to our context it is very important, as well as very useful, to specify informative proper prior distributions for the model parameters. Since there are only a handful of elections in the post-war U.S. history, any non-sample information in the form of theoretical considerations or other historical evidence can play a vital role in producing a proper and well-identified posterior distribution, even though the likelihood function may be poorly identified (Poirier 1998). The prior not only defines the a priori degree of plausibility of the possible parameter values, but also leads to finite sample inferences, given that asymptotic approximations are inadequate because of the small sample sizes we must deal with. Moreover, the prior distribution is an essential ingredient in the calculation of formal model comparison criteria such as marginal likelihoods, Bayes factors, and posterior odds, and therefore plays a vital role in comparing alternative models.

²The two recessions that started under Democrats—one under Truman and the other under Carter—started more than 8 quarters after elections. The economy was in a recession during the first two months of Kennedy’s administration, but that recession started in the last part of Eisenhower’s administration.
In our analysis the prior distributions take the form $\Sigma \sim IW(\nu_0, R_0)$ and $\beta \sim T N_{\{\beta \in S\}}(b_0, B_0)$, so that $\beta$ is restricted to the region of stationarity $S$. Proper formulation of the model requires that we specify values for the hyperparameters $\nu_0$, $R_0$, $b_0$, and $B_0$. To produce informative and credible priors, we use information from a training sample to infer values for the prior hyperparameters of the macroeconomic system, and draw on theoretical considerations to establish priors for the parameters of the vote share equation. Typically, training samples are formed by splitting the data sample into two parts—a training sample and a comparison sample. The model is fit using the training sample, and the resulting posterior density, which embodies the information from the training sample, is used as a proper informative prior density for inference and model choice in the analysis of the comparison sample. In our setting, however, setting aside even a small part of the U.S. data leads to exacerbation of the already severe micronumerosity problem of having too few elections on which to base inferences. We therefore turn to the alternative of establishing training sample priors by studying similar economies. The intuition is that economies would be expected to behave similarly provided their institutional setup and cultural heritage do not differ much, an intuition that is implicitly built in settings involving cross-country regressions and comparisons. To obtain a training sample prior for the macroeconomic parameters in our model, we focused on U.K. data. Specifically, our training sample priors are formed using data from the U.K. from 1997 to 2005 under Tony Blair’s government, a period when the U.K. and U.S. pursued similar economic policies. However, to guard against the problem of specifying unreasonable priors, our results will be subjected to sensitivity analysis as discussed below.

To be comparable to the U.S. data, the U.K. sample involves observations on seasonally adjusted output growth, unemployment, inflation, and interest rates. Output (GDP) growth is calculated from a gross value added output index. The U.K. Retail Prices Index, the most familiar general purpose measure of U.K. inflation of goods and services, is used in the inflation calculation, whereas the interest rate is inferred from the three month sterling treasury bills discount rates. The U.K. data are taken as a “training sample” and estimates based on that sample form the basis for setting the hyperparameters for our training sample prior for the macroeconomic part of the U.S. model. To account for possible heterogeneity across countries, we inflate the variances of the training sample prior derived from the U.K. data before applying it in the U.S. case similarly to the way in which a time-varying parameter model allows for variability in coefficients (i.e. $\beta_{us} = \beta_{uk} + u$, where
\( \text{var} (\mathbf{u}) = \tau \mathbf{I} \). The results of the analysis were checked for sensitivity to the choice of prior by varying the variance-inflation factor \( \tau \) from \( \tau = 0 \) (no variance inflation) through moderate values \( \tau \in (0.05, 0.2) \) to diffuse priors \( \tau = 10 \). The results we present in our subsequent discussion are for \( \tau = 0.1 \), which roughly doubles the training sample variances for most parameters. Since the macroeconomic part of our system contains enough observations, the data are very informative and the posterior estimates and the main facets of our macroeconomic analysis are robust to the choice of \( \tau \). While such robustness is a welcome feature of our analysis, we caution against misinterpreting it as a reason to work with non-informative or improper priors: marginal likelihoods and Bayes factors are not defined under improper priors and the probabilistic calculus that leads to finite sample Bayesian inference is invalidated by such modelling.

The prior distributions in the vote share equation are calibrated based on theoretical considerations along with historical evidence. In an important theoretical article, Palfrey and Rosenthal (1983) develop a game-theoretical model of voter turnout, in which they show that for large electorates, there are only two types of equilibria. In one equilibrium, turnout approaches zero percent; in the other, the percentage turnout approaches twice the minority side’s percentage of the electorate. As a result, they conclude that “elections can be relatively close, even when one alternative is supported by a substantial majority of the electorate,” because “majorities have greater incentives to free-ride”. Therefore, the phenomenon that expected plurality approaches zero is more pervasive than the one that the majority will simply win. Hence, no matter what the initial majority may be, we expect a close vote outcome. Moreover, close election outcomes are consistent with the median voter theory (Black 1948, Downs 1957), which suggests that in order to maximize their chances of election success, parties will aim to appeal to the median voter. An implication of the theory under the assumption that voters cast their votes for either candidate with equal probability when they are indifferent is that parties should get roughly half of the votes in a two-party system. Indeed, vote share for either parity has mostly ranged between 30% to 70% in the historical sample of U.S. presidential and congressional elections (Kastellec, Gelman, and Chandler 2006), while a smaller range (40% – 60%) is used as a basis for simulation in political forecasting (Bafumi, Erikson, and Wlezien 2006). Since our dependent variable \( y_{pt} = \Phi^{-1}(\text{vote share}_t) \) is a non-linear transformation of the observed vote share, we calibrate the model by simulation to find that \( \text{var} (\nu_t) = \Sigma_{22} = 0.1 \) is a sensible value for the expected variance of the error \( \nu_t \) in Equation 4.
This is a cautious choice since it assigns prior mass of 0.9 to the range 30% to 70% of vote shares that is theoretically relevant, but does not absolutely rule out values outside that interval. The priors for $\beta_p$ are centered at zero with a variance of 1, so that the prior does not \textit{a priori} favor one party over the other. The priors constructed this way were used in estimation and our results were tested for sensitivity by variance inflation techniques discussed in the preceding paragraph.

Before concluding our discussion of the data, we wish to emphasize the importance of avoiding “over-conditioning” on additional covariates that can potentially represent policy instruments of the government. Inclusion of such policy instruments in the regression is unwarranted because how else is the government supposed to impact outcomes other than through the use of its policy instruments? For this reason, our current context does not involve variables such as wars, oil prices, or various international agreements. An important theoretical model of war as a tool for opportunistic pre-election behavior is discussed in Hess and Orphanides (1995, 2001a, 2001b). As Beck (1982) remarks “there are no compelling reasons to rule out war as an instrument of macroeconomic policy... if the Democrats cause lower unemployment by getting into wars, they are still causing lower unemployment. Decisions about whether or not to fight wars are not conceptually different from decisions about domestic policies that have economic implications.” To put it another way, the foreign policy of a government is still a policy tool with macroeconomic ramifications that ought to be ascribed to the government that effects them.

4 Estimation Results and Implications

4.1 Assessing Model Uncertainty

Our empirical strategy for studying the behavior of the system in (5) is to address both model and parameter uncertainty. To account for model uncertainty, we evaluated several competing models that differ in terms of their explanatory variables. Four areas of model uncertainty were addressed by comparing models for the macroeconomic system that capture competing hypotheses about the proper model specification; three types of competing models were entertained for the vote share part of the model. We turn to the details next.

The first area of model uncertainty in the macroeconomic system has to do with determination its dynamics – the number of lags of $y_{mt} = (g_t, u_t, i_t, \pi_t)'$ in the macroeconomic system (1) was established by computing marginal likelihoods for models with lag length ranging from 1 to 5.
The baseline model with lag length of one overwhelmingly outperformed longer lag models as its log-marginal likelihood of $-1761.81$ exceeded the log-marginal likelihoods of larger models by at least 40, implying Bayes factors of at least $e^{40}$ in favor of the VAR(1) specification.

Second, the macroeconomic system (1) was estimated in two ways – once as specified in (1) with $z_{t-1}$ on the right hand side, and once with a contemporaneous value of the political indicator $z_t$ are a covariate. For the overwhelming part of our sample the two variables, $z_{t-1}$ and $z_t$, are actually equal – they may potentially differ only in the first quarter of a presidential term (right after elections). The goal of evaluating these two competing models is to see whether the data favor a quick adjustment in the economy, or whether political variables affect the economy with a lag. There seems to be some evidence, although not overwhelming, that $z_{t-1}$ has stronger empirical relevance – the posterior odds of the two types of models are approximately 3 : 1 in favor of $z_{t-1}$ versus $z_t$. The main results of the paper are robust to either specification, and we will present evidence from both types of models.

The third area of model uncertainty in the macroeconomic system has to do with the role of the Fed. Partisan influence from a presidential administration can also affect monetary policymaking by Presidential appointments to the Feds’ Board of Governors (Chappell, Havrilesky, and McGregor, 1993). While the institutional setup in the U.S. allows presidents to appoint their own cabinet in a way that they find convenient (subject to congressional approval), the appointment of the Chairman and the Board of Governors of the Federal Reserve System can have lingering effects. The long 14-year term of appointment for Board members is intended to allow Fed independence of the government, but it holds the possibility to impact the economic policy of subsequent presidential administrations. For this reason, we estimate a model that includes a Fed Chairman dummy that takes the value 1 if the original appointment was by a Republican President and 0 otherwise. The behavior of all macroeconomic variables were similar to those in models without a Fed Chairman dummy, but the marginal likelihood results indicate that inclusion of this variable in the model is not supported by the data – the log-marginal likelihoods were below $-1772.00$, indicating Bayes

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3Six Chairmen of the Fed served during the period covered in our sample: Thomas B. McCabe was originally appointed by President Truman and served Apr 15, 1948–Apr 2, 1951; William McChesney Martin, Jr. was originally appointed by President Truman and served Apr 2, 1951–Feb 1, 1970; Arthur F. Burns was appointed by President Nixon and served Feb 1, 1970–Jan 31, 1978; G. William Miller was appointed by President Carter and served Mar 8, 1978–Aug 6, 1979; Paul A. Volcker was originally appointed by President Carter and served Aug 6, 1979–Aug 11, 1987; Alan Greenspan was originally appointed by President Reagan and served Aug 11, 1987–Jan 31, 2006. The current Chairman of the Fed, Ben Bernanke, was appointed on Feb 1, 2006, after the end of our sample period.
factors of over $e^9$ in favor of the model without a Fed dummy. This conclusion supports recent results in Drazen (2000b) and Faust and Irons (1999) that monetary policy is unlikely to be the main transmission channel of partisan influence and political business cycles in the United States.

The final area of model uncertainty that we explore in the context of the macroeconomic system has to do with testing for differences between the first and second halves of the 4-year presidential term. To do so, we estimate a model that also involves half-term dummies for each party. Such dummies are intended to capture opportunistic behavior by the government (Nordhaus 1975) and the effects of mid-term congressional elections (Alesina and Rosenthal 1989, Alesina et al. 1993). Formal model comparisons, however, do not reveal any significant difference in the economic performance in the two halves of a presidential term – the log marginal likelihood of the model with half-term dummies equals $-1778.22$, which is over 15 less than the model without half-term dummies, indicating a Bayes factor of $e^{15}$ in favor of the latter. The result indicates that the dynamics of the macroeconomic system capture its evolution quite well without the need for additional dummies. Moreover, the result is consistent with the model of economic growth and vote shares in Alesina et al. (1993), in which the President plays a main role and midterm elections are used to counter-balance presidential power.

We also considered two types of competing models in the vote share equation (4). One vote share model is based on the specification in Fair (1996), and contains an intercept, an incumbent dummy $z_{t-1}$, average growth in the two quarters before the general election, $g_t$, average inflation in the two years prior to the general election, $\bar{\pi}_t$, and the interaction terms $\bar{g}_t z_{t-1}$ and $\bar{\pi}_t z_{t-1}$. The last two covariate interactions extend the specification in the direction of allowing for possibly asymmetric effects, which is important because if parties cater to different electorates the presence of different loss functions for each electoral subgroup may cause asymmetries in voter response to economic conditions. As an alternative to this first specification, we consider a second vote share specification which includes war casualty data based on Hibbs (2000, 2007). In particular, the second specification includes an intercept, an incumbent dummy $z_{t-1}$, average growth in the two quarters before the general election, war casualties $f_t$ measured by the cumulative number of American military fatalities in ongoing wars during the term before election, and the interaction terms of $g_t z_{t-1}$ and $f_t z_{t-1}$. Both models performed well – the log-marginal likelihood of the model

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4 More specifically, in our specification the variable $f_t$ includes cumulative U.S. military fatalities per 10,000 population over the Presidential term preceding the election. The casualties are counted for the party initiating the
for \( \mathbf{y}_t = (\mathbf{y}_{mt}', \mathbf{y}_{pt}')' \) in which \( \mathbf{y}_{pt} \) depends on \( z_{t-1}, \bar{g}_t, \) and \( \bar{\pi}_t, \) was -1763.0, while the log-marginal likelihood of the model in which \( \mathbf{y}_{pt} \) depends on \( z_{t-1}, \bar{g}_t, \) and \( \bar{\pi}_t, \) was -1761.8. These results lead to a respective model odds ratio of approximately 1 : 3, which we view as suggestive, although not decisive evidence in favor of including war casualties instead of inflation. For this reason we present results for both specifications in our subsequent discussion.

The aforementioned vote share equations were compared to a third group of more richly parameterized models, which were intended to gauge whether restricting attention to only two measures of economic performance (\( \bar{g}_{t-1} \) and \( \bar{\pi}_{t-1} \)) in the first specification, and only a single measure (\( \bar{g}_{t-1} \)) in the second, is adequate for vote share determination. We therefore compared the two models to ones that also involved the remaining macroeconomic indicators. However, the marginal likelihoods for the two baseline specifications were greater than those of the corresponding more richly parameterized models by approximately 7 on the log scale, providing strong support for the more parsimonious equations.

Taken together, the model comparisons considered in this section have led to the eventual consideration of four models, which, together with their log marginal likelihoods, are presented in Table 2. Results for these models and their implications will be discussed next.

<table>
<thead>
<tr>
<th>Model</th>
<th>Macro Covariates</th>
<th>Vote Share Covariates</th>
<th>ln(marginal likelihood)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mathcal{M}_1 )</td>
<td>(1, ( y_{m,t-1}, z_{t-1} ))</td>
<td>(1, ( z_{t-1}, \bar{g}<em>{t-1}, \bar{\pi}</em>{t-1}, \bar{g}<em>{t-1}z</em>{t-1}, \bar{\pi}<em>{t-1}z</em>{t-1} ))</td>
<td>-1763.0</td>
</tr>
<tr>
<td>( \mathcal{M}_2 )</td>
<td>(1, ( y_{m,t-1}, z_{t-1} ))</td>
<td>(1, ( z_{t-1}, \bar{g}<em>{t-1}, \bar{f}</em>{t-1}, \bar{g}<em>{t-1}z</em>{t-1}, \bar{f}<em>{t-1}z</em>{t-1} ))</td>
<td>-1761.8</td>
</tr>
<tr>
<td>( \mathcal{M}_3 )</td>
<td>(1, ( y_{m,t-1}, z_t ))</td>
<td>(1, ( z_{t-1}, \bar{g}<em>{t-1}, \bar{\pi}</em>{t-1}, \bar{g}<em>{t-1}z</em>{t-1}, \bar{\pi}<em>{t-1}z</em>{t-1} ))</td>
<td>-1764.2</td>
</tr>
<tr>
<td>( \mathcal{M}_4 )</td>
<td>(1, ( y_{m,t-1}, z_t ))</td>
<td>(1, ( z_{t-1}, \bar{g}<em>{t-1}, \bar{f}</em>{t-1}, \bar{g}<em>{t-1}z</em>{t-1}, \bar{f}<em>{t-1}z</em>{t-1} ))</td>
<td>-1763.0</td>
</tr>
</tbody>
</table>

### 4.2 Parameter Estimates and Dynamic Behavior of the Economy

As a consequence of the model comparison results of Section 4.1, we concentrate our discussion on models \( \mathcal{M}_1 \) through \( \mathcal{M}_4 \) – Table 3 presents parameter estimates for \( \mathcal{M}_1 \) and \( \mathcal{M}_2 \) and Table 4 shows the results for \( \mathcal{M}_3 \) and \( \mathcal{M}_4 \). To avoid any confusion over the interpretation of these results, we emphasize that two models for the joint system for \( \mathbf{y}_t = (\mathbf{y}_{mt}', \mathbf{y}_{pt}')' \) were fit in each case; the reason war, while presidents who inherit a conflict from a previous administration get a one-term exemption. For further details, see Hibbs (2000, 2007).
that only one set of results appears for \( y_{mt} \) in each set of results is that the macroeconomic system is well identified so that variations in the specification of the equation for \( y_{pt} \) exercise virtually no influence on the estimates of the VAR parameters.

Table 3: Parameter estimates for models \( \mathcal{M}_1 \) and \( \mathcal{M}_2 \), where \( z_{t-1} \) enters the specification of the macroeconomic system.

<table>
<thead>
<tr>
<th>Response</th>
<th>Constant</th>
<th>( g_{t-1} )</th>
<th>( u_{t-1} )</th>
<th>( i_{t-1} )</th>
<th>( \pi_{t-1} )</th>
<th>( z_{t-1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g_t )</td>
<td>.09</td>
<td>.26</td>
<td>.23</td>
<td>-.10</td>
<td>-.01</td>
<td>-.44</td>
</tr>
<tr>
<td></td>
<td>(.23)</td>
<td>(.06)</td>
<td>(.04)</td>
<td>(.03)</td>
<td>(.09)</td>
<td>(.13)</td>
</tr>
<tr>
<td>( u_t )</td>
<td>.42</td>
<td>-.22</td>
<td>.93</td>
<td>.02</td>
<td>-.01</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(.09)</td>
<td>(.02)</td>
<td>(.02)</td>
<td>(.01)</td>
<td>(.03)</td>
<td>(.05)</td>
</tr>
<tr>
<td>( i_t )</td>
<td>.12</td>
<td>.14</td>
<td>.01</td>
<td>.96</td>
<td>.05</td>
<td>-.21</td>
</tr>
<tr>
<td></td>
<td>(.17)</td>
<td>(.05)</td>
<td>(.03)</td>
<td>(.02)</td>
<td>(.07)</td>
<td>(.10)</td>
</tr>
<tr>
<td>( \pi_t )</td>
<td>.10</td>
<td>.11</td>
<td>-.03</td>
<td>.08</td>
<td>.51</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(.16)</td>
<td>(.04)</td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.09)</td>
</tr>
</tbody>
</table>

From Tables 3 and 4, we see that the parameter estimates under the four model specifications are very similar, especially so in terms of the macroeconomic system. Moreover, we see that the estimates in the macroeconomic system align closely with generally accepted notions of short-run macroeconomic behavior where, for example, higher GDP growth in one quarter is associated with lower unemployment, higher GDP growth, inflation and interest rate in the following period, higher unemployment rate in a quarter is associated with lower interest rates and inflation in the next, and so on. The effects of the political dummies (\( z_{t-1} \) and \( z_t \)) correspond closely to the conclusions of the political business cycle literature for the short-run partisan effects. The tables also reveal that the macroeconomic series are characterized by persistent, highly dynamically dependent behavior.

To gain visual insight into the estimation results, Figure 1 presents the marginal posterior distributions (and the corresponding priors) for the parameters of models \( \mathcal{M}_1 \) and \( \mathcal{M}_2 \) (the plots
Table 4: Parameter estimates for models $M_3$ and $M_4$, where $z_t$ enters the specification of the macroeconomic system.

<table>
<thead>
<tr>
<th>Macroeconomic System under Models $M_3$ and $M_4$</th>
<th>Response</th>
<th>Constant</th>
<th>$g_{t-1}$</th>
<th>$u_{t-1}$</th>
<th>$i_{t-1}$</th>
<th>$\pi_{t-1}$</th>
<th>$z_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$g_t$</td>
<td>.11</td>
<td>.28</td>
<td>0.21</td>
<td>-.10</td>
<td>-.01</td>
<td>-.34</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.23)</td>
<td>(.06)</td>
<td>(.04)</td>
<td>(.03)</td>
<td>(.09)</td>
<td>(.12)</td>
<td></td>
</tr>
<tr>
<td>$u_t$</td>
<td>.41</td>
<td>-.22</td>
<td>.93</td>
<td>.02</td>
<td>-.01</td>
<td>0.12</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.09)</td>
<td>(.02)</td>
<td>(.02)</td>
<td>(.01)</td>
<td>(.03)</td>
<td>(.05)</td>
<td></td>
</tr>
<tr>
<td>$i_t$</td>
<td>.13</td>
<td>.15</td>
<td>.00</td>
<td>.97</td>
<td>.04</td>
<td>-.20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.17)</td>
<td>(.05)</td>
<td>(.03)</td>
<td>(.02)</td>
<td>(.07)</td>
<td>(.10)</td>
<td></td>
</tr>
<tr>
<td>$\pi_t$</td>
<td>.11</td>
<td>.11</td>
<td>-.02</td>
<td>.08</td>
<td>.51</td>
<td>0.03</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.16)</td>
<td>(.04)</td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.08)</td>
<td></td>
</tr>
</tbody>
</table>

Vote Share Equation: $M_3$

<table>
<thead>
<tr>
<th>Response</th>
<th>Constant</th>
<th>$z_{t-1}$</th>
<th>$\bar{g}_{t-1}$</th>
<th>$\bar{g}<em>{t-1} z</em>{t-1}$</th>
<th>$\bar{\pi}_{t-1}$</th>
<th>$\bar{\pi}<em>{t-1} z</em>{t-1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_{p,t}$</td>
<td>-.10</td>
<td>.21</td>
<td>-.05</td>
<td>.09</td>
<td>.15</td>
<td>-.21</td>
</tr>
<tr>
<td></td>
<td>(.30)</td>
<td>(.32)</td>
<td>(.18)</td>
<td>(.17)</td>
<td>(.23)</td>
<td>(.22)</td>
</tr>
</tbody>
</table>

Vote Share Equation: $M_4$

<table>
<thead>
<tr>
<th>Response</th>
<th>Constant</th>
<th>$z_{t-1}$</th>
<th>$\hat{g}_{t-1}$</th>
<th>$\hat{f}_{t-1}$</th>
<th>$\hat{g}<em>{t-1} z</em>{t-1}$</th>
<th>$\hat{f}<em>{t-1} z</em>{t-1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_{p,t}$</td>
<td>-.01</td>
<td>.04</td>
<td>-.11</td>
<td>.06</td>
<td>.18</td>
<td>-.16</td>
</tr>
<tr>
<td></td>
<td>(.14)</td>
<td>(.17)</td>
<td>(.13)</td>
<td>(0.09)</td>
<td>(.17)</td>
<td>(1.01)</td>
</tr>
</tbody>
</table>

for models $M_3$ and $M_4$ are visually similar and have been omitted). An inspection of Figure 1 indicates that the parameters are well estimated and that significant learning has taken place based on the U.S. data relative to the priors that were specified in Section 3. The one poorly identified parameter in the figure appears to be the coefficient on $f_{t-1} z_{t-1}$ in model $M_2$. While some learning has indeed taken place relative to the prior, it is relatively small because Republicans in the sample led wars that had far fewer fatalities than the two large military conflicts in Korea and Vietnam, which saw large escalations under Democrats.\(^5\)

Interpretation of the coefficients in Tables 3 and 4 beyond their impact in the very short run is complicated by the dynamic interaction among the economic variables in this system. While we see that the short-run effects of Republican presidents is to lower growth and employment, it is also important to note that interest rates also decline. Standard new Keynesian analysis suggests

\(^5\)Hibbs (2007) has argued that the war casualty variable is quite important for the 1952 and 1968 elections that took place during the Korean and Vietnam wars, respectively. However, given that in recent decades warfare has evolved in the direction of substituting high monetary costs for human costs, the construction of a new measure of the costs of war would appear to be a worthwhile area for future research.
that in future periods these lower interest rates will spur economic growth and employment, e.g. by reducing crowding out in capital markets and stimulating investment. In addition, increased unemployment may serve to dampen increases in inflation, which in turn may lead to higher growth and employment in the future. Because of such interactions and feedback effects, the intermediate- and long-term macroeconomic effects need not have magnitudes, or even signs, that are similar to those in the short-run.

To understand the intermediate- and long-term effects, we study the evolution of the dynamic system of macroeconomic and political outcomes. We approach this as a forecasting problem based on equations (1) and (4) and the parameter estimates in Tables 3 and 4. Due to the discrete nature of political outcomes, prediction is non-standard and is therefore approached by simulation. Specifically, conditionally on a political regime, forecasts of the macroeconomic variables are realized from (1) and those, in turn, enter equation (4) in election periods to provide relative vote shares.
and determine the next political regime. As a result, we are able to evaluate the steady state of (1) and the evolution path through which the economy gets there. The evolution of the system will be examined in detail shortly, but for the discussion of steady states, we mention that the vote share forecasts from equation (4) suggested a consistent small advantage for the incumbent party (approximately 53%-56% of the two-party vote share). In this case, one can directly solve for the steady states of the system by simple algebraic manipulation of the VAR(1) system in (1) yielding the following two steady states:

\[ y_{mt}^D = (I - F_{m1})^{-1} \mu_m, \quad \text{(under a Democratic President)}, \]  
\[ y_{mt}^R = (I - F_{m1})^{-1} (\mu_m + G_m), \quad \text{(under a Republican President).} \]

The above expressions provide the limiting values of simulation-based steady state forecasting method described above. These expressions can be evaluated using draws of \( F_{m1}, \mu_m \) and \( G_m \) from the main MCMC run or at particular parameter values such as the posterior means or medians to obtain the implied steady state values of output growth, unemployment, interest, and inflation. Because the long-run outcomes are a non-linear function of the parameters (since (8) and (9) involve matrix inversion) and Jensen’s inequality applies, one has to be mindful of the fact that the posterior expected value of each partisan steady state will differ somewhat from the steady state computed at the posterior means of the parameters. For this reason, we present both – the steady state values and summaries of their posterior distribution are given in Table 5.

The central message of all models in Table 5 is that the long-run outcomes are very different from the results in the existing political business cycle literature, where estimation is mostly done one-equation-at-a-time. The key point of these results is that eventual Republican macroeconomic outcomes appear to be superior in all respects. For example, Table 5 reveals that for models \( M_1 \) through \( M_4 \), the mean differences in quarterly GDP growth are in the range 0.12–0.21 percentage points—or 0.48–0.84 annually—higher under Republicans (the corresponding median differences are 0.07–0.17, or 0.28 to 0.68 annually, percentage points higher). The long-run Republican unemployment rate is 1.26 to 1.32 percentage points lower at the mean (0.80 to 0.85 at the median). The steady state outcomes under Democrats exhibit much higher rates of interest and inflation – the interest rate difference is approximately 7.9 points at the mean and 6.5 to 6.6 at the median, while the difference in quarterly inflation is 1.25–1.31 points (or 6 to 6.2 points annually) at the mean, or
1.02 to 1.07 at the median. Because we have draws from the finite sample distribution of the steady states, we can also compute the probability that the difference is in favor of one party or the other. This is done in the last column of Table 5, which lists the posterior probabilities that Republican steady state values are larger than Democratic ones. These are finite sample probabilities of an event, and should not be confused with significance levels in hypothesis testing. According to the outcomes of models $M_1$ through $M_4$, eventual output growth under Republicans is preferable to that under Democrats with probability 0.69 to 0.85; a similar conclusion holds for unemployment, where that probability is approximately 0.7. Quite noticeably, these probabilities are much stronger for nominal interest and inflation, where the long-run Democratic interest rates and inflation are higher with probabilities exceeding 0.97 and 0.96, respectively.

We remark that it is important to distinguish the computation of steady states from that of impulse response functions that many macroeconomists may be familiar with. The steady states give the long-term dynamic equilibrium of the system, whereas the impulse responses show the behavior of the system as it is shocked from that long-run equilibrium by some structural shock. Moreover, the computation of impulse responses implicitly assumes that a steady state actually exists and the dynamic system has achieved it. As a result, the computation of steady states is actually less demanding than that of impulse responses because the latter also require an orthogonalization of the disturbances into structural shocks – an issue that is irrelevant in the

### Table 5: Steady state (SS) distribution summaries for the economic indicators. The table also includes steady states computed at the posterior mean of the parameters $(SS_{E(\beta|y)})$.

<table>
<thead>
<tr>
<th>variable</th>
<th>Republican SS</th>
<th>Democratic SS</th>
<th>probabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>med</td>
<td>SD</td>
</tr>
<tr>
<td>$g$</td>
<td>0.90</td>
<td>0.88</td>
<td>0.11</td>
</tr>
<tr>
<td>$u$</td>
<td>5.28</td>
<td>5.46</td>
<td>1.18</td>
</tr>
<tr>
<td>$i$</td>
<td>1.76</td>
<td>2.28</td>
<td>3.12</td>
</tr>
<tr>
<td>$\pi$</td>
<td>0.42</td>
<td>0.52</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Models $M_1$ and $M_2$

Models $M_3$ and $M_4$

| $g$      | 0.94 | 0.92 | 0.12 | 0.92 | 0.73 | 0.75 | 0.16 | 0.75 | 0.85 |
| $u$      | 5.26 | 5.44 | 1.21 | 5.43 | 6.58 | 6.29 | 1.53 | 6.30 | 0.29 |
| $i$      | 1.79 | 2.33 | 3.18 | 2.33 | 9.68 | 8.86 | 3.98 | 8.84 | 0.03 |
| $\pi$   | 0.40 | 0.50 | 0.56 | 0.49 | 1.71 | 1.57 | 0.71 | 1.57 | 0.03 |
computation of steady states.

In order to clarify the short- and intermediate-run implications of the parameter estimates for the behavior of output growth, unemployment, nominal interest, and inflation, we plot the evolution of macroeconomic outcomes in Figures 2 (for models $M_1$ and $M_2$) and Figure 3 (for models $M_3$ and $M_4$). Starting from the sample averages for the economic variables, the figure traces the evolution of each variable under Democrats and Republicans.

![Graphs showing quarterly GDP growth, unemployment rate, nominal interest rate, and quarterly inflation rate for Democrats and Republicans.](image)

**Figure 2:** Economic forecasts under models $M_1$ and $M_2$ for each party (variables are expressed in percentage points).

The Figures clearly show that economic growth improves in the immediate aftermath of a Democratic victory, and the converse is true for Republicans. The short-run results therefore are in full agreement with the findings reported in the existing literature. From an econometric perspective, it is rather remarkable that this divergence is captured without the need for half-term dummies, but emerges as a result of the dynamic evolution of the system. The widest divergence in quarterly GDP growth between the two paths is realized after three quarters, at which point the quarterly growth rate under Democratic presidency is 0.5 percentage point higher than that
under Republican presidency, amounting to 2 percentage points difference in the annualized growth rate. After that, however, the difference shrinks and, depending on the model, reversal occurs 10 to 12 quarters into the Presidential term. The quarterly growth rates achieve steady state and their difference stabilizes at 24 quarters and beyond. In contrast, the largest divergence in unemployment occurs later than that for GDP growth, when the difference grows to be approximately 1 percentage point. The two unemployment rates converge thereafter and achieve reversal in approximately 42 to 46 quarters. Interest rates and inflation, on the other hand seem to be consistently higher on a Democratic watch and no reversals take place.

While there may well be other political-economic interpretations of these dynamic relationships, their behavior is consistent with an intertemporal trade-off between “immediate gratification” (with a long-term cost attached to it) and the promise of long-term benefits that come at the cost of a short-term economic slowdown. This is different than the simple trade-off between output growth and inflation in the static case, and is consistent with the existence of differences in intertemporal

Figure 3: Economic forecasts under models $M_3$ and $M_4$ for each party (variables are expressed in percentage points).
preferences among the two parties, who now have to balance costs and benefits that occur at different point of time.

Turning attention to the estimates of the vote share equations in Tables 3 and 4, we note that the function \( y_{pt} = \Phi^{-1}(\text{voteshare}) \) takes a non-linear form, making direct interpretation of the coefficients difficult. To facilitate interpretation and evaluate the effect of economic variables, we calculate the marginal effects on the respective vote shares of a one percentage point increase in annual output growth and inflation, as well as the effect of incumbency.\(^6\) Our computations show that an increase in annual GDP growth of one percentage point before the election would affect the vote share for a Republican incumbent by 0.69 to 0.94 percentage points, and would increase the vote share for a Democratic incumbent by 0.49 to 1.1 percentage points. These effects are in line with those found in Fair (1978), in which a 1 percentage point increase in the annual growth rate increases the vote share for the incumbent party by about 1 percentage point. Both parties appear to be punished when inflation increases on their watch. The effect of one percentage point increase in annual inflation is stronger for Republicans (the vote share for a Republican incumbent will decrease by 1.23 percent points) than it is for Democrats (the vote share for a Democratic incumbent is predicted to decrease by 0.89 percentage points). The results also reveal a strong incumbency effect – all else equal, models \( M_1 \) through \( M_4 \) predict that the incumbent vote share will tend to be between 4.5 and 5.4 percentage points higher than for the candidate of the opposite party. We do caution, however, that due to the large posterior standard deviations of the parameters in the vote share equations, the marginal effects are not precisely estimated and should be interpreted accordingly.

4.3 Alternation of Power

The results of Section 4.2 illustrate that the expected long-run outcomes under Republicans dominate Democratic steady states. Those results were derived by examining the joint behavior of the macroeconomic and political outcomes as provided by the formal empirical model. In this section we examine a different scenario for the purposes of illustration of the effects of the frequency with which the Presidency vacillates between Republicans and Democrats. This is an interesting issue

\(^6\)The marginal effects are computed at the sample averages of the data and the posterior means of the parameters for models \( M_1 \) through \( M_4 \). While the war casualty effects become meaningful at magnitudes such as the Vietnam or Korean wars, they do not have a distinguishable effect on vote shares at low levels that may be more appropriate for more modern conflicts.
because as shown in Section 4.2, the macroeconomic variables exhibit different speed of convergence – while GDP growth tends to evolve relatively rapidly, the evolution of unemployment is much slower and takes longer than the typical inter-election period. In particular, here we examine the case where the electoral advantage to the incumbent party is overturned by external shocks and study the observed dynamic evolution of the economy as a function of how frequently the Presidency vacillates between Republicans and Democrats.

To get a sense of these oscillation effects, we describe the behavior of the economy when presidents alternate either after four years (one presidential term) or eight years (two presidential terms). The resulting economic fluctuations are given in Figures 4 and 5 for four-year alternative terms, and Figures 6 and 7 when presidents are replaced after 8 years. One noticeable aspect of Figures 4 and 5 is that in the one-term case the long-term cross-overs in output growth are just barely visible, and the behavior of unemployment does not suggest that a reversal is likely in the future. In this scenario, the short-run effects are dominant under all models and Democrat outcomes appear much more appealing – output grows faster, unemployment is lower, and the costs of high interest and inflation rates seem relatively small. However, in the two-term scenario, when the long-run effects have had time to materialize, we see that GDP grows faster in the second Republican term and that unemployment is beginning to decline, even though two terms is not long enough for a reversal to take place. However, now the costs of higher inflation and interest rates are more visible because the magnitudes of the respective differences are larger.

Three additional observations deserve attention. The first is that the economy becomes more volatile when partisan oscillations occur at relatively smaller intervals, just as one might expect – within twenty years, we observe more than two business cycles under the 4-year regime and only one business cycle under the 8-year regime. A second observation is that the depth of the cycles varies. While output growth is characterized by quick adjustments and one can not see any significant differences in the magnitude of those cycles, we do see that unemployment, interest, and inflation vary more widely under the two-term scenario that in the single-term case. This can be attributed to their slower adjustment relative to GDP growth and leads to the view that longer presidential terms may lead to fewer, but relatively more pronounced, fluctuations of economic aggregates. Finally, the figures show that even if the economy is in a high-growth, low-inflation Republican steady state, significant short-run benefits exist in moving to a short-run Democratic equilibrium. This reveals
Figure 4: Economic performance under one-term alternation (models $M_1$ and $M_2$).

Figure 5: Economic performance under one-term alternation (models $M_3$ and $M_4$).
Figure 6: Economic performance under two-term alternation (models $M_1$ and $M_2$).

Figure 7: Economic performance under two-term alternation (models $M_3$ and $M_4$).
the potential for time inconsistency, and raises the possibility that intertemporal heterogeneity in voter discount rates can be an important factor in election outcomes.

4.4 Covariance Matrix of the Errors

We present the covariance matrix of the error terms in Table 6. From this table, we can calculate how deviation in the unemployment above its expectation would change real GDP growth. This is done using the formula for the conditional mean of GDP growth

\[ E(g_t|u_t) = E(g_t) + \sigma_{ug}\sigma_{uu}^{-1}(u_t - E(u_t)) \]

Here \( \sigma_{ug} \) is the covariance between \( u_t \) and \( g_t \), and \( \sigma_{uu} \) is the variance of \( u \). Table 6 shows that \( \sigma_{ug} = -0.17 \) and \( \sigma_{uu} = 0.11 \), therefore, we obtain that one percentage point increase in unemployment above the natural rate corresponds to a decrease in GDP growth of 1.55 (\(-0.17/0.11\)) percentage points. This estimate is smaller than previous empirical findings for Okun’s law, which have suggested that for every percentage point by which actual unemployment rate exceeds its “natural” rate, real GDP is reduced by 2 to 3 percent; however, our estimate is consistent with work by Blanchard (1989) who finds a similar magnitude in a VAR framework.

Table 6: Covariance matrix of the errors

<table>
<thead>
<tr>
<th></th>
<th>( g_t )</th>
<th>( u_t )</th>
<th>( i_t )</th>
<th>( \pi_t )</th>
<th>( z_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g_t )</td>
<td>.77</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( u_t )</td>
<td>-0.17</td>
<td>.11</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( i_t )</td>
<td>0.14</td>
<td>-0.08</td>
<td>.50</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( \pi_t )</td>
<td>0.01</td>
<td>-0.01</td>
<td>0.14</td>
<td>.37</td>
<td>-</td>
</tr>
<tr>
<td>( z_t )</td>
<td>.04</td>
<td>-.01</td>
<td>-.004</td>
<td>-.01</td>
<td>.03</td>
</tr>
</tbody>
</table>

By the same token, we can calculate an expectations augmented Phillips curve, the relation between unexpected inflation \((\pi_t - \pi_t^e)\), which is the error in the inflation equation, and unemployment \( u_t \), using

\[ E(u_t|\pi_t) = E(u_t) + \sigma_{u\pi}\sigma_{\pi\pi}^{-1}(\pi_t - \pi_t^e) \]

Since \( \sigma_{u\pi} = -0.01 \) and \( \sigma_{\pi\pi} = .37 \), we have \( \sigma_{u\pi}\sigma_{\pi\pi}^{-1} = -0.01/.37 = -0.027 \). Therefore, a 1 percentage point increase in unanticipated inflation corresponds to a decrease in unemployment of 0.027 percentage points.

Table 7 shows the correlation matrix of the error terms. There are sizable error correlations between GDP growth and unemployment, interest rate and unemployment, interest rate and inflation, and GDP growth and vote share. We can see that the disturbances underlying the economic and political processes are interrelated and not independent, supporting the case for joint modelling.
Table 7: Correlation matrix of the errors

<table>
<thead>
<tr>
<th></th>
<th>( g_t )</th>
<th>( u_t )</th>
<th>( i_t )</th>
<th>( \pi_t )</th>
<th>( z_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( g_t )</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( u_t )</td>
<td>-0.59</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( i_t )</td>
<td>0.23</td>
<td>-0.33</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( \pi_t )</td>
<td>0.02</td>
<td>-0.07</td>
<td>0.31</td>
<td>1.00</td>
<td>-</td>
</tr>
<tr>
<td>( z_t )</td>
<td>0.26</td>
<td>-0.15</td>
<td>-0.04</td>
<td>-0.07</td>
<td>1.00</td>
</tr>
</tbody>
</table>

and estimation.

5 Concluding Remarks

This paper has studied the evolution of macroeconomic and political outcomes in the post-war United States using a joint dynamic system designed to capture the role of macroeconomic interactions, as well as the feedback between political and economic variables. We find important partisan differences in both the short run and the long run. The short-run differences are consistent with those found in the earlier literature on political business cycles. However, the long-run outcomes are likely to be characterized by an important reversal in the rates of output growth and unemployment relative to the short-run partisan effects; moreover, forecasts from the model suggest that the long run partisan differences for inflation and interest rates are likely to be much wider than those in the short run. Our results indicate that with real-world election frequencies, a reversal is likely to be observed for output growth, but not for unemployment, as in the case of the latter variable convergence takes much longer to achieve than the usual Presidential term. For the electoral part of the model, we find suggestive evidence that both economic and non-economic variables (e.g. growth, war fatalities) are relevant and can improve predictions of vote shares relative to conditioning solely on economic outcomes (e.g. growth and inflation).

These results identify the impact of a fundamental economic constraint on political action: that government actions can possibly increase consumption either in the short or the long run, but that doing so on both occasions is not possible. We hope that our research will therefore be a step towards framing the debate in terms of choices between feasible intertemporal outcomes rather than short-run static comparisons. While additional data on longer stretches of one-party ruling would help pinpoint the short- and long-run effects of partisan outcomes, the models in this paper have

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pierced beyond the veil of frequent party oscillations to offer predictive distributions supporting
the contention that both types of effects do, in fact, exist.

An important aspect of our analysis has been the implementation of Bayesian econometric
techniques, which has offered a number of advantages in the current setting. These advantages
include finite sample inferences for the model parameters and functions thereof (e.g. long-run outcomes), the ability to compute model probabilities for model choice and model averaging of
nested and non-nested models, and the ability to include out-of-sample information to deal with the
problem of microminority that arises due to the small number of elections in the post-war period.
Although the Bayesian methodology used here is fairly simple, it goes a long way towards eliciting
the effects and interactions we wish to study. While the model considered herein has incorporated
the interdependence between macroeconomic outcomes and political regimes, an important item
for future research would be to consider the potential for structural breaks or regime-switching in
the macroeconomy (Sims and Zha 2006) or political outcomes (Jones, Kim, and Startz 2007).

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