Advance Access publication March 25, 2009

Political Analysis (2009) 17:113–142
doi:10.1093/pan/mpp001

Modeling Macro-Political Dynamics

Patrick T. Brandt
School of Economic, Political and Policy Sciences, The University of Texas at Dallas
800 W. Campbell Road, GR 31, Richardson, Texas 75080
e-mail: pbrandt@utdallas.edu (corresponding author)

John R. Freeman
Department of Political Science, University of Minnesota,
1414 Social Science Building, 267 19th Ave. South, Minneapolis, MN 55455
e-mail: freeman@umn.edu

Analyzing macro-political processes is complicated by four interrelated problems: model scale, endogeneity, persistence, and specification uncertainty. These problems are endemic in the study of political economy, public opinion, international relations, and other kinds of macro-political research. We show how a Bayesian structural time series approach addresses them. Our illustration is a structurally identified, nine-equation model of the U.S. political-economic system. It combines key features of the model of Erikson, MacKuen, and Stimson (2002) of the American macropolity with those of a leading macroeconomic model of the United States (Sims and Zha, 1998; Leeper, Sims, and Zha, 1996). This Bayesian structural model, with a loosely informed prior, yields the best performance in terms of model fit and dynamics. This model 1) confirms existing results about the countercyclical nature of monetary policy (Williams 1990); 2) reveals informational sources of approval dynamics: innovations in information variables affect consumer sentiment and approval and the impacts on consumer sentiment feed-forward into subsequent approval changes; 3) finds that the real economy does not have any major impacts on key macropolity variables; and 4) concludes, contrary to Erikson, MacKuen, and Stimson (2002), that macropartisanship does not depend on the evolution of the real economy in the short or medium term and only very weakly on informational variables in the long term.

1 Introduction

Many political scientists are interested in modeling macro-political systems. Aggregate public opinion research focuses on a small number of opinion variables and some economic variables. Political economists analyze data on policy and economic outcomes of interest to voters, outcomes that are functions of underlying political variables. International relations scholars typically model the behavior of belligerents over time to analyze the evolution of cooperation and conflict.

Authors' note: A previous version of this paper was presented at the 2005 Annual Meeting of the American Political Science Association, Washington, DC, and at a seminar at the College of William and Mary. The authors thank Janet Box-Steffensmeier, Harold Clarke, Brian Collins, Chetan Dave, Larry Evans, Jeff Gill, Simon Jackman, and Ron Rappoport for useful feedback and comments. Replication materials, additional appendices, and additional results are available on the *Political Analysis* Web site or from P.T.B. The authors are solely responsible for the contents.

Modeling macro-political dynamics in these varied research areas is complex for four reasons. The first is the problem of *scale*. By scale, we mean the number of (potentially) endogenous variables in a model. Macro-political systems are composed of many variables and of multiple causal relationships. To capture these relationships, several equations are needed. For instance, in American political economy one must take into account the relationships between public opinion variables and partisanship, and between these variables and economic output, employment, and prices. Each relationship requires a separate, dynamic equation. Similarly, students of international relations must account for the behavioral relationships of all important belligerent groups within and between countries. A separate equation is needed for each directed, dyadic behavior.

A closely related, second problem is *endogeneity*. Although some variables in macro-political processes clearly are exogenous, we believe that others are both a cause *and* a consequence of each other. For example, our understanding of democracy implies that there is some popular accountability for economic policy and thus endogeneity between popular evaluations of the economy and macroeconomic outcomes (or policies).

Persistence is a third problem. Some variables are driven by short-term forces that can be exogenous to the macro-political process under study. There also are deeper, medium, and long-term forces that make trends in variables persist and even create long-term, common trends among variables (e.g., cointegration).

Finally, *specification uncertainty* is a problem. We have no equivalent of macroeconomics' General Equilibrium Theory that can help us specify functional forms. The problems of scale, endogeneity, and persistence mean that models have many coefficients and that their dynamic implications (impulse responses) and forecasts have wide error bands (i.e., are quite imprecise). Because of these problems, our models may also tend to overfit our data.

None of the approaches commonly used to model dynamic processes in political science together addresses all four problems. The most common macro-models are single-equation autoregressive distributed lag (ADL) models and pooled time series cross-sectional (TSCS) regressions. These single-equation models expressly omit multiple relationships among endogenous variables. Common practice is to make each relationship the subject of a different article (or book chapter). This treats each variable as a dependent in one article (chapter) and independent variable in another.[1] Users of ADL and TSCS models usually acknowledge endogeneity problems, but rarely perform exogeneity tests. Rather *ad hoc* solutions to this problem are used like omitting contemporaneous relationships between variables, temporally aggregating data, and employing contrived variables for simultaneity. Some researchers use instrumental variable estimators for this purpose but rarely evaluate the adequacy of their instruments. Also, treatments of persistence often are based on knife-edged pretests for unit roots. Perhaps it is not surprising then that Wilson and Butler (2007) recently reported that the results of many published articles that use single-equation TSCS models are not robust to simple changes in model specification.[2]

[1]For a recent review of ADL and single-equation models, see De Boef and Keele (2008).

[2]In international political economy it is common to put on the right-hand-side of a single equation explaining a particular policy variable in country i, the average level of the same variable in all other countries (*sans* i). Franzese and Hays (2005) propose a better approach to TSCS modeling based on spatial statistics. However, they only consider endogeneity for one variable. Wilson and Butler (2007) focus on the assumptions macro-political theorists make about unit effects and first-order dynamics in simple single-equation TSCS models. They note that if assumptions of exogeneity also were evaluated along with the possibility of more complex dynamics (longer lag lengths, nonstationarity, etc.), the results reported in many published works are likely to be even less robust (see especially pp. 115–6, 120).

Reduced form (RF) vector autoregression (VAR) representations of simultaneous equation models address these scale and endogeneity issues. Some users of RFs in comparative political economy analyze models with three to four variables (or equations) where all variables are endogenous. The problem is that most macroeconomists now argue that there are many more key relationships in markets. Models with more variables are needed to capture macroeconomic dynamics (e.g., Leeper, Sims, and Zha 1996). We know of no work in international political economy with a RF model on this scale, for instance, a model that includes three to four equations for *each* of three or four trading partners (cf. Sattler, Freeman, Brandt 2008, 2009).[3] Students of international conflict have built RF models with 24–28 equations, but restrict their investigations to simple (Granger) causality testing. They do not use their models to study conflict dynamics or to produce forecasts because without some restrictions on the model the specification uncertainty renders the dynamic responses quite imprecise.[4]

Finally, users of simulation methods such as Erikson, MacKuen, and Stimson (2002, chap. 10) and Alesina, Londregan, and Rosenthal (1993) address the scale and persistence issues. But they expressly eschew endogeneity, making restrictions that treat macro-political processes as (quasi-)recursive. Moreover, these researchers often do not produce meaningful measures of precision in their dynamic analyses, for example, no error bands for their impulse responses.[5]

Table 1 summarizes some the models used to address the four problems discussed above. As we move from VAR models on the left, to Bayesian VAR, and finally to the new model that is potentially more useful than current macro-political models, in the Bayesian Structural Vector Autoregression (B-SVAR) we see that we can address all four problems. Part one of the paper explains the nature of the B-SVAR model, distinguishing it from more familiar RF models like frequentist VAR, vector error correction model (VECM), and also BVAR, and explaining how it addresses the four problems listed in Table 1. The rationale for using elucidated, informed priors rather than uninformed or older ''Minnesota'' priors is explained in this part. The criteria used to evaluate the performance of B-SVARs and of the informed prior in their specifications also is explained here.[6]

Part two shows how this model can be used to analyze the American macro-political economy. We construct a nine-equation, structurally identified Bayesian time series model of the U.S. political-economic system. This model combines key features of the model of Erikson, MacKuen, and Stimson (2002, chap. 10) of the American macropolity with those of a leading neo-Keynesian U.S. macroeconomic model (Leeper, Sims, and Zha 1996; Sims and Zha 1998). This structural model, with a loosely informed prior, yields the best performance in terms of model fit and dynamics. This loose prior model 1) confirms existing results about the countercyclical nature of monetary policy (Williams 1990), 2) reveals informational sources of approval dynamics: innovations in information variables

[3]Franzese (2002) pools time series for countries in a VECM. While simultaneously addressing issues of scale and persistence, it is not clear how (if) he handles endogeneity within and between countries.

[4]Examples of these larger-scale RF models in international relations are Goldstein and Pevehouse (1997), Pevehouse and Goldstein (1999), and Goldstein et al. (2001).

[5]Erikson, MacKuen, and Stimson (2002, 386) refer to endogeneity as a ''nuisance'' and a ''nightmare.'' Their analysis imposes strong restrictions—some contemporaneous relationships are ignored and a recursive structure—on the interrelationships between variables and on their lag specifications. This is despite their argument that feedback is a defining feature of the macro-political economy. Erikson, MacKuen, and Stimson also provide no error bands for their impulse responses.

[6]Our 2006 paper in *Political Analysis* explained modern BVAR models and how to use them in innovation accounting, forecasting, and policy analysis. The focus in the present paper is on B-SVAR models and on the more general problem of modeling and identifying macro-political processes.

Table 1 RF, Bayesian, and structural models of macro-politics

	Models		
Problems	VAR/VECM (RF)	BVAR (Bayesian)	B-SVAR (Bayesian and structural)
Scale (typical)	4–6 Equations	6–8 Equations	8–18 Equations
Endogeneity	Recursive/decomposition of the endogenous relationships	Recursive/decomposition of the endogenous relationships	Theoretically implied contemporaneous relationships that may be nonrecursive and/or overidentified
Persistence and dynamics	Pretests for lag length, unit roots, and cointegration	Elucidated informed prior for random walks; dummy variable priors for persistence and cointegration	Elucidated informed prior for random walks, persistence, and cointegration, conditional on contemporaneous identification
Specification uncertainty	Pretesting; "Let data speak"	Elucidated equation-by-equation prior that generates a nonstandard posterior density	Theoretically informed structural identification and yields a system-wide prior with a tractable conditional posterior densities
Political science examples	Edwards and Wood (1999), Goldstein et al. (2001)	Williams (1993a), Williams and Collins (1997)	Brandt, Colaresi, and Freeman (2008), Sattler, Freeman, and Brandt (2008)
Econometric references	Sims (1972, 1980)	Doan, Litterman, and Sims (1984), Litterman (1986)	Leeper, Sims, and Zha (1996), Sims and Zha (1998)

affect consumer sentiment and approval and the impacts on consumer sentiment feed-forward into subsequent approval changes, 3) finds that the real economy does not have any major impacts on key macropolity variables, and 4) concludes that, contrary to Erikson, MacKuen, and Stimson (2002), macropartisanship does not depend on the evolution of the real economy in the short or medium term and only very weakly on informational variables in the long term. In the spirit of the Bayesian approach (Gill 2004, 2007; Jackman 2004, 2008), we believe that these results are insensitive to alternative specifications of prior beliefs, including beliefs motivated by the late-1990s macropartisanship debate. Directions for extending the Bayesian structural time series approach to macro-political analysis and to linking it with formal theory are discussed briefly in the conclusion.

2 Bayesian Time Series Models and the Study of Macro-political Dynamics

Following the publication of Sims (1980) seminal article on macroeconomic modeling, political scientists began exploring the usefulness of RF methods such as VAR (Freeman, Williams, and Lin 1989; Williams 1990; Brandt and Williams 2007). This approach holds that macro-theory is not strong enough to specify the functional forms of equations. Macro-theory is at best a set of loose causal claims that translate into a weak set of model restrictions. Therefore, progress in macro-theory results from analyzing RF models and subjecting these models to (orthogonalized) shocks in the respective variables (e.g., innovation accounting or impulse responses). If there are any structural implications of theories, they are best represented as contemporaneous relationships between our variables, but then only as zero restrictions (Bernanke 1986). In the last 20 years, this approach has been applied to a wide range of topics in political science such as agenda setting, public opinion, political economy, and international conflict.

A parallel development in political science is the use of the Bayesian methods. This approach rests on two main premises: 1) political phenomena are inherently uncertain and changing and 2) available prior information should be used in model specification (Gill 2004, 324). Bayesianism stresses systematically incorporating previous knowledge into the modeling process, being explicit about how prior beliefs influence specification and results, making rigorous probability statements about quantities of interest, and gauging sensitivity of the results to a model's assumptions (ibid. 333–4).[7]

Here we bring these two developments together. We show how 1) the Bayesian approach makes time series analysis both more systematic and informative and 2) how prior information about dynamics and contemporaneous relationships can be utilized.

2.1 *Bayesian Structural Vector Autoregessions*

We first present a multiple-equation model for the relationships among a set of endogenous variables. Our goal in employing such a system of equations is to isolate the *behavioral* interpretations of the equations for each variable by imposing structure via restrictions on the system of equations.[8] The contemporaneous structure of the system is important for two reasons. First, it identifies (in a theoretical and statistical sense) these possible contemporaneous relationships among the variables in the model. Second, restrictions on the structural relationships imply short- and long-term relationships among the variables.

The basic model we propose for macro-political data has one equation for each of the endogenous variables in the system. Each of the endogenous variables is a function of the contemporaneous (time "0") and p past (lagged) values of all the endogenous variables in the system. This produces a dynamic simultaneous equation model that can be written in matrix notation as,

$$\underset{1\times m}{Y_t}\ \underset{m\times m}{A_0} \sum_{\ell=1}^{p} \underset{1\times m}{Y_{t-\ell}}\ \underset{m\times m}{A_\ell} = \underset{1\times m}{d} + \underset{1\times m}{\varepsilon_t} \qquad t = 1, 2, \ldots, T, \tag{1}$$

with each vector's and matrix's dimensions noted below the matrix. This is an m-dimensional VAR for a sample size of T, with y_t a vector of observations for m variables at time t, A_ℓ the coefficient matrix for the ℓth lag, $\ell = 1, \ldots, p$, p the maximum number of lags (assumed known), d a vector of constants, and ε_t a vector of i.i.d. normal *structural shocks* such that

[7]Gill (2004, 333–4) lists seven features of the Bayesian approach. Only four of these are mentioned in the text. Others include updating tomorrow's priors on the basis of today's posteriors, treating missing values in the same way as other elements of models like parameters, and recognizing that population quantities change over time. Jackman (2004) explains how frequentist and Bayesian approaches differ but also how, under certain conditions, their inferences can "coincide" (e.g., when the prior is uniform, the posterior density can have the same shape as the likelihood). See also Gill (2004, 327–28).

[8]This structure and the equations themselves start from an unrestricted VAR model. The goal is to impose plausible restrictions on the contemporaneous relationships among the variables. Zha (1999) considers restrictions on lagged values of the variables.

$$E[\varepsilon_t | y_{t-s}, s > 0] = \underset{1\times m}{0}, \text{ and } [\varepsilon_t' \varepsilon_t | y_{t-s}, s > 0] = \underset{m\times m}{I}.$$

Equation (1) is a structural VAR or SVAR. Two sets of coefficients in it need to be distinguished. The first are the coefficients for the lagged or past values of each variable, $A_\ell, \ell = 1, \ldots, p$. These coefficients describe how the dynamics of past values are related to the current values of each variable. The second are the coefficients for the *contemporaneous* relationships (the "structure") among the variables, A_0. The matrix of A_0 coefficients describes how the variables are interrelated to each other in each time period (thus the time "0" impact). For example, if the data are monthly, these coefficients describe how changes in each variable within the month are related to one another. Relationships exist outside of that month (in the past) are described by the A_ℓ (lag) coefficients. The contemporaneous coefficient matrix for the structural model is assumed to be nonsingular and subjects only to linear restrictions.[9] Zero restrictions on elements of A_0 imply that the respective variables are unrelated contemporaneously.

This model is estimated via multivariate regression methods (Sims and Zha 1998; Waggoner and Zha 2003a). The Bayesian version of this model or B-SVAR incorporates informed beliefs about the dynamics of the variables. These beliefs are represented in a prior distribution for the parameters. Sims and Zha (1998) suggest that the prior for A_ℓ is conditioned on the specification decision for A_0.[10] To describe the prior, we place the corresponding elements of A_0 and the A_ℓ into vectors. For a given A_0, contemporaneous coefficient matrix, let a_0 be a vector that is the columns of A_0 stacked in column-major order for each equation. For the A_ℓ parameters that describe the lag dynamics, let A_+ be an $(m^2p + 1) \times m$ matrix that stacks the lag coefficients and then the constant (rows) for each equation (columns). Finally, let a_+ be a vector that stacks the columns of A_+ in column major order (so the first equation's coefficient, then the second equation's, etc.). The prior over a_0 and a_+, denoted $\pi(a)$ is then,

$$\pi(a) = \pi(a_0)\phi(\tilde{a}_+, \Psi), \tag{2}$$

where the tilde denotes the mean parameters in the prior density for a_+, $\phi(\cdot, \cdot)$ is a multivariate normal with mean $\tilde{a}_+$ and covariance Ψ.[11]

Sims and Zha's (1998) prior for equation 2 addresses the main problems of macromodeling. For example, the prior addresses the scale problem by putting lower probability on the coefficients of the lagged effects, thus shrinking these parameters toward zero. But rather than imposing (possibly incorrect) exact restrictions on these coefficients such as

[9]Here we use the word "structural" to define a model that is a dynamic simultaneous system of equations with the contemporaneous relationships identified by the A_0 matrix.

[10]This prior is a revised version of the "Litterman" or "Minnesota" prior for RF VAR models (Litterman 1980; Doan, Litterman, and Sims 1984; Brandt and Freeman 2006). Doan, Litterman, and Sims (1984, 2, 4, respectively) originally referred to the Minnesota prior as a "standardized prior" or "empirical prior". Today, empirical macroeconomists say the prior is based on their extensive experience in forecasting economic time series and "widely held beliefs" about macroeconomic dynamics (e.g., Sims and Zha 1998, fn. 7). In this sense, it resembles the first prior discussed by Jackman (2004). Empirical macro-economists call the Sims-Zha hyperparameters a "reference prior." Their use of the term thus is more consistent with convention in their discipline (Zellner and Siow 1980) than in statistics (Bernardo 1979). Finally, such priors also can be elicited (Kadane, Chan, and Wolfson 1996). However, in empirical macroeconomics, the prior almost always is elucidated as a widely held belief. An exercise of this type in political science is Western and Jackman (1994).

[11]When the prior in equation (2) has a symmetric structure (i.e., it differs by only a scale factor across the equations), the posterior conditional on A_0 is multivariate normal. See Kadiyala and Karlsson (1997), Sims and Zha (1999), and Brandt and Freeman (2006).

zeroing out lags or deleting variables altogether, the prior imposes a set of inexact restrictions on the lag coefficients. These inexact restrictions are prior beliefs that many of the coefficients in the model—especially those for the higher order lags—have a prior mean of zero. The prior is then correlated across equations in a way that depends on the contemporaneous relationships between variables (the covariance of RF disturbances via the A_0 matrix of the SVAR). This allows beliefs about the identification of systems such as the macro-political economy to be included *a priori* and thus improve inferences and forecasting. Finally, the prior is centered on a random walk model: it is based on the belief that most time series are best explained by their most recent values.[12]

The Sims-Zha prior parameterizes the beliefs about the conditional mean of the coefficients of the lagged effects in a_+ given a_0 in equation (2). Once more, the prior mean is assumed to be that the best predictor of a series tomorrow is its value today. The conditional prior covariance of the parameters, $V(a_+|a_0) = \Psi$ is more complicated. It is specified to reflect the following beliefs about the series:

1. The standard deviations (SDs) around the first lag coefficients are proportional to those for the coefficients of all other lags.
2. The weight of each variable's own lags in explaining its variance is the same as the weights on other variables' lags in an equation.
3. The SDs of the coefficients of longer lags are proportionately smaller than those of the coefficients of earlier lags. Lag coefficients shrink to zero over time and have smaller variance at higher lags.
4. The SD of the intercept is proportionate to the SD of the residuals for the equation.[13]

A series of hyperparameters are used to scale the SD of the model coefficients to reflect these and other beliefs. Table 2 summarizes the hyperparameters in the Sims-Zha prior.[14] The key feature of this specification is that the interdependence of beliefs is reflected in the conditioning of the prior on the structural contemporaneous relationships, A_0. Beliefs about the parameters are correlated in the same patterns as the RF contemporaneous residuals. If for theoretical reasons we expect large correlations in the RF innovations of two variables, the corresponding regressors are similarly correlated at the first lag to reflect this belief and to ensure that the series move in a way that is consistent with their unconditional correlations.[15]

The posterior density for the model parameters is then formed by combining the likelihood for equation (1) and the prior:

$$\Pr\left(A_0, A_\ell, \ell = 1, \ldots, p\right) \propto \phi\left(a_+, a_0 \middle| Y\right) \phi\left(\tilde{a}_+, \Psi\right) \pi\left(a_0\right). \tag{3}$$

Estimation and sampling from the model's posterior is via a Gibbs sampler. The main complication in the Gibbs sampler is the sampling from the over-identified cases of the

[12]This does *not* mean we are assuming the data follow a random walk. Instead, it serves as a benchmark for the prior. If it is inconsistent with the data, the data will produce a posterior that does not reflect this belief.

[13]The scale of these SDs is determined by a series of univariate AR(p) regressions for each endogenous variable. The hyperparameters then scale the SDs from the AR(p) regressions for the prior.

[14]Hyperparameters μ_5 and μ_6 have to do with beliefs about dynamics. We explain them in the next section of the paper.

[15]Sims and Zha (1998, 955) write "Thus if our prior on [the matrix of structural coefficients for contemporaneous relationships among the variables] puts high probability on large coefficients on some particular variable j in equation i, then the prior probability on large coefficients on the corresponding variable j at the first lag is high as well."

Table 2 Hyperparameters of Sims-Zha reference prior

Parameter	*Range*	*Interpretation*
λ_0	[0,1]	Overall scale of the error covariance matrix
λ_1	> 0	SD about A_1 (persistence)
λ_2	$= 1$	Weight of own lag versus other lags
λ_3	> 0	Lag decay
λ_4	$\geqslant 0$	Scale of SD of intercept
λ_5	$\geqslant 0$	Scale of SD of exogenous variables coefficients
μ_5	$\geqslant 0$	Sum of autoregressive coefficients component
μ_6	$\geqslant 0$	Correlation of coefficients/initial condition component

contemporaneous A_0 coefficients. Waggoner and Zha (2003a) show how to properly draw from the posterior of A_0 given the identification restrictions that may be imposed on the A_0 coefficients. We have implemented this Gibbs sampler for the full set of posterior coefficients. We employ it here to estimate our B-SVAR model of the American political economy.[16]

A key feature of the B-SVAR model is that its contemporaneous restrictions affect the dynamic parameters. This can be seen by examining the RF of the structural model in equation (1). The RF representation of the B-SVAR is written in terms of the contemporaneous values of the (endogenous) variables and their (weakly exogenous or predetermined) past values,

$$y_t = c + y_{t-1}B_1 + \cdots + y_{t-p}B_p + u_t, \; t = 1, 2 \ldots, T. \tag{4}$$

This is an m-dimensional multivariate time series model for each observation in the sample, with y_t an $1 \times m$ vector of observations at time t, B_ℓ the $m \times m$ coefficient matrix for the ℓth lag, and p the maximum number of lags. In this formulation, all the contemporaneous effects (which are in the A_0 matrix of the SVAR) are included in the covariance of the RF residuals, u_t.

The RF in equation (4) is derived from the SVAR model by post-multiplying equation (1) by A_0^{-1}. This means that the RF parameters are transformed from the structural equation parameters via

$$c = \mathrm{d}A_0^{-1}, B_\ell = -A_\ell A_0^{-1}, \; \ell = 1, 2, \ldots, p, \; u_t = \varepsilon_t A_0^{-1}, \tag{5}$$

where the last term in equation (5) indicates how linear combinations of structural residuals are embedded in the RF residuals. As equation (5) shows, restricting elements of A_0 to be zero restricts the linear combinations that describe the RF dynamics of the system of equations via the resulting restrictions on B_ℓ and u_t.

These restrictions also affect the correlations among the RF residuals. This is because zero restrictions in A_0 affect the interpretation and computation of the variances of the RF residuals:

[16]Distinctive priors could be formulated for each equation, but then a more computationally intensive importance sampling method must be used to characterize the posterior of the model (Sims and Zha 1998). Because the Sims-Zha prior applies simultaneously and has a conjugate structure for the entire system of equations, one can exploit the power of a Gibbs sampler.

$$\mathrm{Var}(u_t) = E[u_t^{'}u_t] = E[(\varepsilon_t A_0^{-1})^{'}(\varepsilon_t A_0^{-1})] = E[(A_0^{-1^{'}})\varepsilon_t^{'}\varepsilon_t A_0^{-1}] = A_0^{-1^{'}}A_0^{-1} = \Sigma. \quad (6)$$

In a standard RF analysis, A_0^{-1} is specified as a just-identified triangular matrix (via a - Cholesky decomposition of Σ) so there is a recursive, contemporaneous causal chain among the equations. A maximum likelihood method can be used to estimate the RF parameters of the model, and from these parameters the elements of the associated A_0 can be ascertained.[17]

For SVARs, the A_0 is typically nonrecursive and overidentified. Frequentist estimation uses a maximum likelihood estimation for the nonrecursive contemporaneous relationships in the parameters of A_0 (Bernanke 1986; Sims 1986b; Blanchard and Quah 1989). This procedure uses the RF residual covariance Σ in equation (6) to obtain estimates of the elements of A_0. In either frequentist or Bayesian approaches to estimation, the RF covariance Σ always has $[m \times (m + 1)]/2$ free parameters. Thus, A_0 also can have no more than $[m \times (m + 1)]/2$ free parameters. Models for which A_0 has less than $[m \times (m + 1)]/2$ free parameters or, equivalently, more than $[m \times (m + 1)]/2$ zero restrictions, are called overidentified.[18]

Nonrecursive restrictions on A_0 amount to two sets of constraints on the model. First, specifying elements of A_0 as zero means that the equations and variables corresponding to the rows and columns of A_0 are contemporaneously uncorrelated. Second, since the RF coefficients B_ℓ, which describe the evolution of the dynamics of the model, are themselves a function of the structural parameters (and their restrictions) in equation (5), the restrictions in A_0 propagate through the system over time. In other words, the restrictions on the contemporaneous relationships in the model in A_0 have both short-term and long-term effects on the system.

Since A_0 and B_ℓ describe the RF dynamics of the system, the B-SVAR restrictions also affect the estimates of the impulse responses which are the moving average representation of the impact of shocks to the model. These responses, C_{t+s} describe how the system reacts in period $t + s$ to a change in the RF residual u_s at time $s > t$. These impulse responses are computed recursively from the RF coefficients and A_0:

$$\frac{\partial y_{t\,+\,s}}{\partial u_s} = C_s = B_1 C_{s-1} + B_2 C_{s-2} + \cdots + B_p C_{s-p}, \quad (7)$$

with $C_0 = A_0^{-1}$ and $B_j = 0$ for $j > p$. Since these impulse are functions of the RF coefficients B_ℓ, and $B_\ell = -A_\ell A_0^{-1}$, the structural restrictions in A_0 are present in the dynamics of the RF of the model.

The interpretation of the impulse responses for SVAR models differs from those of RF VAR models. In the latter one typically employs a Cholesky decomposition of the Σ matrix, which is a just identified, recursive model. In this case, all the shocks hitting the system have the same (positive) sign and enter the equations, but according to the ordering of the variables in the Cholesky decomposition. Systems with a Cholesky

[17]The RF maximum likelihood case, where A_0^{-1} is a Cholesky decomposition of Σ, implies a recursive or Wold causal chain between the disturbances. This Cholesky decomposition exists because the RF error covariance matrix Σ is positive definite. For a discussion and application of the concept of a Wold causal chain in political science, see Freeman, Williams, and Lin (1989) or Brandt and Williams (2007).

[18]To estimate nonrecursive A_0's, it is necessary to satisfy both an order and a rank condition as detailed in Hamilton (1994, 1994, section 11.6). (Note that as regards Hamilton's formulation, in our case his D matrix is an identity matrix.) In our illustration below, the numerical optimization of the posterior peak requires that the rank condition is satisfied.

decomposition have a triangular structure where the shocks make each left-hand-side variable in the system move in a positive direction. With the Cholesky, decomposition shocks in equations are uniquely related to shocks in variables. In an SVAR system, because there are no unique left-hand-side variables, there is no unique correspondence between shocks in variables and shocks to equations. Thus, shocks to a given equation can be positive or negative as a result. One could normalize the shocks to be a particular sign, but this is merely selecting among the modes of the posterior of the coefficients in A_0. This "sign normalization" complicates the sampling of the model but leaves the interpretation of the orthogonal shocks in the SVAR unchanged for the respective impulse responses.[19]

2.2 *Modeling Macro-Political Dynamics*

This B-SVAR model is quite general and it subsumes a number of well-known models as special cases: ADL models, error correction models, ARIMA models, RF and simultaneous equation models, etc. (for details, see Brandt and Williams 2007). This generality allows us to address the four main problems of macro-modeling outlined earlier.

Complexity and Model Scale: Modeling politics as a system requires an analyst to specify a set of state variables and the causal connections between them.[20] The problem is that as more variables are needed to describe a system, the usefulness of the model diminishes. The model proposed in equation (1) for m variables can have $m^2p + m$ estimable coefficients in A_+ and up to $[m \times (m + 1)]/2$ coefficients in A_0. This is a large number of parameters—even for small choices of m and p (if $m = 6$ and $p = 6$, this would be 237 parameters). The flexibility of the model comes at a cost: higher degrees of parameter uncertainty relative to the available degrees of freedom.[21]

The results of this cost are that inferences tend to be rather imprecise. So efforts to assess the impact of political and economic variables on each other may produce null findings because of a lack of degrees of freedom relative to the number of parameters. These problems arise because large, unrestricted models tend to overfit data. For example, they attribute too much impact to the parameters on distant lags.[22] One solution is to restrict the number of endogenous variables in the model and to restrict the dynamics by limiting the number of lagged values in the model. As noted in the Introduction, political scientists who study macro-political dynamics are comfortable with the concept of a (sub)system whether in terms of the macropolity (Erikson, MacKuen, and Stimson 2002) or international conflict (Goldstein et al. 2001). But these restrictions are problematic because they are often *ad hoc* and can lead to serious inferential problems (Sims 1980).

[19]For discussion of the implications of sign normalization, see Waggoner and Zha (2003a). This is discussed below in the interpretation of our illustration. It also surfaces in applications of the B-SVAR model to the Israeli-Palestinian conflict (Brandt, Colaresi, and Freeman 2008).

[20]A system is a "particular segment of historically observable reality [that] is mutually interdependent and externally, to some extent, autonomous" (Cortes, Przeworski, and Sprague, 1974, 6). And the state of a dynamic system, as embodied in a collection of state variables, is "the smallest set of numbers which must be specified at some [initial time] to predict uniquely the behavior of the system in the future" (Ogata 1967, 4).

[21]A contrast to this is item-response theory models that are used to model ideological scales. There the number of parameters is large and helps in fitting the model of multiple responses.

[22]Sampling error tends to cause the standard errors on distant lag coefficients to be underestimated. For more on the problems associated with increases in model scale relative to the dynamic analysis and forecasting see, Sims and Zha (1998, 958–60), Zha (1998), and Robertson and Tallman (1999, especially, p. 6 and fn. 7).

Using the Sims-Zha prior in a structural VAR model has two distinct advantages. First, it allows us to work with larger systems with a set of informed or baseline inexact restrictions on the parameters. Second, it reduces the high degree of inferential uncertainty produced by the large number of parameters. For instance, the Sims-Zha prior produces smaller and smaller variances of the higher order lags (via λ_3).

Endogeneity and Identification: Political scientists are aware of the problem of simultaneity bias. They also are sensitive to the fact that their instruments may not be adequate to eliminate this bias (Bartels 1991). But when it comes to medium- and large-scale systems, most political scientists are content to make strong assumptions about the exogeneity of a collection of ‘‘independent variables’’ and to impose exact (zero) restrictions on the coefficients of lags of their variables. In cases like the work of Erikson, MacKuen, and Stimson on the American macropolity (2002, chap. 10), an entire, recursive equation systems is assumed.[23]

The deeper problem here is that of identification or structure. In the case of macropolitical analysis, this problem is especially severe because we usually work in nonexperimental settings. Manipulation of variables and experimental controls is not possible. Manski (1995, 3) emphasizes the seriousness of this problem: ‘‘. . . the study of identification comes first. Negative identification findings imply that statistical inference is fruitless . . ..’’ Manski acknowledges endogeneity as one of three effects that make identification difficult.[24]

Structure in a B-SVAR model amounts to the contemporaneous relationships between the variables that one expects to see. Those that are not plausible are restricted to zero (so zeros are placed in appropriate elements of the contemporaneous coefficient matrix A_0) and the remaining contemporaneous relationships are estimated. The real advantages of this modeling approach are as follows: 1) it forces analysts to confront and justify which relationships are present contemporaneously and 2) it imposes restrictions on the paths of the relationships over time. This is particularly relevant in political economy applications. Consider, for instance, a model of monetary policy and presidential approval. Here, economic variables affect monetary policy making and vice versa. Hence, the structural specification has to include economic as well as political relationships. Just as critical is specifying the timing of the impacts of relationships among approval, monetary policy, and the economy (e.g., see Williams (1990)). Some of the variables are likely to be contemporaneously related—for example, approval and monetary policy.

To specify the contemporaneous structure of the B-SVAR model, the equations in the system often are partitioned into groups called ‘‘sectors.’’ These sectors are linear combinations of the contemporaneous innovations as specified in the A_0 matrix. These sectors of variables then are ordered in terms of the speed with which the variables in them respond to the shocks in variables in other sectors. In macroeconomics, some aggregates like output and prices are assumed to respond only with a delay to monetary and other kinds of policy innovations. Restrictions on these contemporaneous relationships therefore imply that the economic output variables are not contemporaneously related to monetary policy. Competing identifications are tested by embedding their implied restrictions on contemporaneous relationships in a larger set of such restrictions and assessing the posterior density of the data with respect to the different identifications. The overidentified and

[23]Erikson, MacKuen, and Stimson do perform a handful of exogeneity tests. See, for instance, the construction of their presidential approval model. But when it comes to analyzing their whole system, they simply *posit* a recursion for their ‘‘historical structural simulation.’’ We elaborate on this point in our illustration.

[24]The other two effects that confound identification are contextual effects and correlation effects.

nonrecursive nature of the A_0 matrix create challenges in estimation and interpretation of the model.[25]

Persistence and Dynamics: Political series exhibit complex dynamics. In some cases, they are highly autoregressive and equilibrate to a unique, constant level. In other cases, the series tend to remember politically relevant shocks for very long periods of time thus exhibiting nonstationarity (i.e., a stochastic trend). In still other cases, these stochastic political trends tend to move together and are thus cointegrated. Political scientists have found evidence of stochastic trends in approval and uncovered evidence that political series are (near) cointegrated (e.g., Ostrom and Smith 1993; Clarke and Stewart 1995; Box-Steffensmeier and Smith 1996; De Boef and Granato 1997; Clarke, Ho and Stewart 2000). Erikson, MacKuen, and Stimson (1998, 2002, chap. 4) make a sophisticated argument about the interpretation of macropartisanship as a nonstationary ‘‘running tally of events.’’ Such arguments reveal these scholars’ beliefs about whether a series will re-equilibrate. How quickly this occurs and the implications for inference are matters of debate.

Our point is that these beliefs are best expressed as probabilistic statements rather than based on knife-edged tests for cointegration or unit roots. One of the benefits of using a Bayesian structural time series model is that it allows us to investigate beliefs about the dynamic structure of the data. If the researcher has a strong belief about the stationarity/nonstationarity of the variables, one can combine this belief with the data and see if it generates a high- or low-probability posterior value (rather than a knife-edged result).

The Sims-Zha prior accounts for these dynamic properties of the data in three ways. The first is by allowing the prior beliefs about SD around the first lag coefficients λ_1 to be small, implying strong beliefs that the variables in the system follow random walks and are non-stationary.[26] The prior allows analysts to incorporate beliefs about stochastic trends and cointegration. Continuing with the enumeration in Table 2, the Sims-Zha prior also includes two additional hyperparameters that scale a set of dummy observations or pre-sample information that correspond to the following beliefs:

1. Sum of autoregressive coefficients component (μ_5): This hyperparameter weights the precision of the belief that average lagged value of a variable *i* better predicts variable *i* than the averaged lagged values of a variable $i \neq j$. Larger values of μ_5 correspond to higher precision (smaller variance) about this belief. This allows for correlation among the coefficients for variable *i* in equation *i*, reflecting the belief that there may be as many unit roots as endogenous variables for sufficiently large μ_5.
2. Correlation of coefficients/initial condition component (μ_6): The level and variance of variables in the system should be proportionate to their means. If this parameter is greater than zero, one believes that the precision of the coefficients in the model is proportionate to the sample correlation of the variables. For trending series, the precision of this belief should depend on the variance of the pre-sample means of the variables in the model and the possibility of common trends among the variables.

[25]The idea that theories imply restrictions on contemporaneous relationships may seem new. But Leeper, Sims, and Zha (1996, 9 ff.) point out that such restrictions are implicit in our decisions to make variables predetermined and exogenous. In terms of the actual estimation, an unrestricted element in A_0 means the data potentially can pull the posterior mode for the respective parameter off its prior (zero) value. In contrast, a zero restriction on an element of A_0 forces the respective posterior mode of that element to be zero.

[26]In the case of stationary data, a ‘‘tight’’ or small value for λ_1 implies a slow return to the equilibrium value of the series. A tight value of λ_4 is a belief in smaller variance around the equilibrium.

Values of zero for each of these parameters imply that both beliefs are implausible. These beliefs are incorporated into the estimation of the B-SVAR using a set of dummy observations in the data matrix for the model. These dummy observations represent stochastic restrictions on the coefficients consistent with the mixed estimation method of Theil (1963). As $\mu_5 \to \infty$, the model becomes equivalent to one where the endogenous variables are best described in terms of their first differences and there is no cointegration. As Sims and Zha explain, because the respective dummy observations have zeros in the place for the constant, the sums of coefficient prior allows for nonzero constant terms or "linearly trending drift." As $\mu_6 \to \infty$, the prior places more weight on a model with a single common trend representation and intercepts close to zero (Robertson and Tallman 1999, 10 and Sims and Zha 1998, section 4.1).

The possibility of nonstationarity makes Bayesian time series distinctive from other Bayesian analyses. In the presence of nonstationarity, the equivalence between Bayesian and frequentist inference need not apply: "time series modeling is . . . a rare instance in which Bayesian posterior probabilities and classical confidence intervals can be in substantial conflict" (Sims and Zha 1995, 2). Further, including these final two hyperparameters and their dummy observations has a number of advantages. First, it means the analyst need not perform any pre-tests that could produce mistaken inferences about the trend properties of her or his data. Instead, one should analyze the posterior probability of the model to see if the fit is a function of the choice of these hyperparameters.[27] Second, claims about near- and fractional integration can be expressed in terms of μ_5 and μ_6. Using these two additional hyperparameters should enhance the performance of macro-political models, especially of models of the macro-political economy.[28] Finally, the inference problems associated with frequentist models of integrated and near-integrated time series are avoided in this approach. Strong assumptions about the true values of parameters are avoided by the use of Bayesian inference and by sampling from the respective posterior to construct credible intervals rather than by invoking asymptotic approximations for confidence intervals.[29]

Model Uncertainty: The problem of model uncertainty is an outgrowth of the weakness of macro-political theory. This uncertainty operates at two levels: theoretical uncertainty and statistical uncertainty. Theoretical uncertainty includes the specification of the model, such things as endogenous relationships. Statistical uncertainty encompasses the uncertainty about the estimated parameters. The uncertainty of these estimates depends on the prior beliefs, the data, and the structure of the model—which itself may be due to indeterminate theoretical structure.

[27]Information about the probability of unit roots and cointegration vectors can be computed from a posterior sample. We could compute lag polynomials for each draw and then look at the implied stationarity and cointegration to get a summary measure of the behavior around the unit circle. In these cases, one might want a prior over such behavior, such as that suggested by Richard (1977). This would be another alternative to the priors suggested in footnote 10.

[28]Robertson and Tallman (1999, 2001) compare the forecasting performance of a wide number of VAR and Bayesian VAR specifications. They find that it is the provision for unit roots and common trends that is most responsible for the improvement in the forecasting performance of their model over unrestricted VARs and over VARs with exact restrictions.

[29]From the Bayesian perspective, nonstationarity is not a nuisance. Williams (1993b) and Freeman et al. (1998) document the problems nonstationarity causes for political inference. The crux of the problem is whether the true values of parameters are in a neighborhood that implies nonstationarity. If they are, in finite samples, normal approximations may be inaccurate as the boundary of the region for stationary parameters is approached. Empirical macroeconomists are reluctant, as we should be, to assume that parameters are distant from this boundary (see Sims and Zha 1995, 2). This problem seems to be overlooked by our leading Bayesians Gill (2004, 328) and Jackman (2004, 486).

Observational equivalence (*viz.*, poor identification) is a consequence of both forms of uncertainities, which are often hard to separate. Too often multiple models explain the data equally well. As the scale of our models increases, this problem becomes more and more severe: models with many variables and multiple equations will all fit the data well (Leeper, Sims, and Zha 1996, 14–15; Sims and Zha 1998, 958–60). Models that are highly parameterized and based on uncertain specifications complicate dynamic predictions. The degree of uncertainty about the dynamic (impulse) responses of medium- and large-scale systems inherits the serial correlation that is part of the endogenous systems of equations. Hence, conventional methods for constructing error bands around them are inadequate (Sims and Zha 1999).[30]

How then do we select from among competing theoretical and statistical specifications? We first need to be able to evaluate *distinct model specifications* or parametric restrictions (e.g., specifications based on different theoretical models, restrictions on lag length, equations, A_0 identification choices). Second, there are a large variety of possible *prior beliefs* for BVAR and B-SVAR models.

Evaluations of model specifications are hypothesis tests and are typically evaluated using some comparison of a model's posterior probability—such as Bayes factors where one compares the prior odds of two (or more) models to the posterior odds of the models. This is appropriate for comparing functional and parametric specifications. Methods that are particularly relevant for (possibly) non-nested and high-dimensional models like the B-SVAR model are model monitoring and summaries of the posterior probabilities of various model quantities (see Gill 2004). These Bayesian fit measures allow us to analyze the hypotheses about specification and other model features without the necessity of nesting models that may be consistent with various theories. One thus easily can compare models on a probabilistic basis.

The evaluation of competing *prior* specifications or beliefs requires comparing different priors and their impacts on posterior distributions of the parameters. This is harder to do, since it is a form of sensitivity analysis to see how the posterior parameters (or hypothesis tests, or other quantities of interest) vary as a function of the prior beliefs. For large-scale models such as B-SVARs, examining the posterior distribution of the large number of individual parameters is infeasible. Although one might desire an omnibus fit statistic such as an R^2 or sum of squared error, such quantities will be multivariate and hard to interpret.

One common suggestion by non-Bayesians is to "estimate" the prior hyperparameters. That is, one should treat the hyperparameters as a set of additional nuisance parameters (e.g., fixed effects) that can be estimated as part of the maximization of the likelihood (posterior) of the model. This is problematic, as Carlin and Louis (2000, 31–2) note: "Strictly speaking, empirical estimation of the prior is a violation of Bayesian philosophy: the subsequent prior-to-posterior updating . . . would 'use the data twice' (first in the prior, and again in the likelihood). The resulting inferences would thus be 'overconfident'."

Further complicating the assessment of prior specification is the nature of time series data itself. Time series data are not a "repeated" sample. This is what causes many of the major inferential problems in classical time series analysis, especially unit root analysis. Williams (1993b, 231) argues that "Classical inference is . . . based on inferring something about a population from a sample of data. In time-series [*sic*], the sample is not random, and the population contains the future as well as past." The presence of unit roots and the

[30]A notable exception here is the item-response models used to create ideological scales for members of Congress and Supreme Court justices (Poole and Rosenthal 1997; Poole 1998; Martin and Quinn 2002). Here adding more parameters actually helps reduce the uncertainty about the underlying ideological indices.

special nature of a time series sample therefore argue against "testing" for the prior. Instead, priors should reflect our beliefs based on past analyses, history, and expectations about the future. They should not then be estimated from the data, as this is only one realization of the data generation process.

In practice, two tools are used to evaluate the structural representation of contemporaneous relationships, A_0, and the priors for the B-SVAR model. The first is the log marginal data density (also known as the log marginal likelihood):

$$\log(m(Y)) = \log(\Pr(Y|A_0, A_+)) + \log(\Pr(A_0, A_+)) - \log(\Pr(A_0, A_+|Y)), \quad (8)$$

where $\log(\Pr(Y|A_0, A_+))$ is the log likelihood of the B-SVAR model, $\log(\Pr(A_0, A_+))$ is the log prior probability of the parameters, and $\log(\Pr(A_0, A_+|Y))$ is the posterior probability of the B-SVAR model parameters. Since a Gibbs sampler is used to sample the B-SVAR model, we can compute the log marginal data density ($\log(m(Y))$ in equation 8 using the method proposed by Chib (1995).[31] These log probabilities of the data, conditional on the model, summarize the probability of the model; they can be computed from the Gibbs sample output (Geweke 2005, chap. 8). Bayes factors can be formed from the log marginal data densities to gauge the relative odds of competing, theoretical representations of contemporaneous political relationships. Again, impluse response analysis is an important complement here. The study of the dynamics of a given structural specification—whether it produces theoretically meaningful and empirically sensible impulse responses—is an integral part of the model evaluation process. Brandt, Colaresi, and Freeman (2008) and Sattler, Freeman, Brandt (2008, 2009) show how to use the log marginal density and impulse responses together to evaluate competing structural specifications of important relationships in international relations and comparative political economy.

The same tools are used to evaluate competing priors for B-SVAR models but with two important caveats. The log marginal data density is only applicable for *informative* priors. Diffuse or improper prior should not be evaluated with this tool. This is because under a diffuse prior, the posterior parameters will have low probability and the in-sample fit will be too good; an inflated estimate of the log marginal data density will be obtained.[32] Also, the impulse responses for diffuse priors almost always are of little use. This is because the scale of these models (in the absence of an informative prior) renders their error bands too large to allow for any meaningful inferences about the causal effects of shocks in one variable on another. The reason for this is that the diffuse prior allows the sampler to search too large a parameter space producing estimates that allow for behavior too far from the sample of interest. This is illustrated in the Appendix.

[31] The quantity estimated for each draw is $\log(m(Y)) = \log(\Pr(Y|A_0, A_+)) + \log(\Pr(A_0, A_+)) - \sum_{i=1}^{m} \log(\Pr(A_0(i), A_+|Y, i \neq j))$, where m is the number of equations, and $A_0(i)$ is the ith column of A_0. Note that we do this computation one column at a time for A_0 per the blocking scheme for computing the log marginal density using the Gibbs sampler (Chib 1995; Waggoner and Zha 2003a).

[32] Chib (1995) notes that the quantity in equation 8 is the log of the *basic marginal likelihood identity*, or

$$m(Y) = \frac{\Pr(Y|A_0, A_+)\Pr(A_0, A_+)}{\Pr(A_0, A_+|Y)}.$$

For the diffuse prior model, the posterior probability of the parameters in the denominator of this expression, $\Pr(A_0, A_+|Y)$ will be small. This will inflate the value for $m(Y)$ and hence also its logarithm. Kass and Raftery (1995) warn against using diffuse priors in Bayes factor calculations. Among their points is "... using a prior with a very large spread ... under [the alternative hypothesis] in an effort to make it 'noninformative' will force the Bayes factor to favor [the null]. This was noted by Bartlett (1957) and is sometimes called 'Bartlett's paradox.' As Jeffrey's recognized, to avoid this difficulty, priors on parameters being tested ... generally must be proper and not have too big a spread." (ibid. 782).

B-SVARs as an approach to modeling macro-politics: B-SVAR modeling presents some challenges for political scientists. First, unlike the case for VAR/VECM models, we must elucidate informed priors that represent the beliefs of the macro-political theorists working on a particular problem. These beliefs must be translated into the hyperparameters described above and the sensitivity of model performance to these translations must be assessed. In contrast to BVAR modeling, B-SVAR modeling also requires us to make theoretically informed specification decisions about the existence of contemporaneous relationships among our variables. To specify the A_0 matrix in the model, we must study and translate theory into an appropriate set of identifying restrictions. In overidentified cases, some computational problems have to be solved.[33]

If these challenges can be met, we will have valuable new tools for macro-political analysis. With these tools, we will be able to analyze political systems of medium scale in new ways—ways that allow for endogeneity but which also incorporate theory and allow tests of insights about the contemporaneous relationships between our variables. In addition, we can avoid the inferential pitfalls of pre-testing used in frequentist time series analysis, such as knife-edge decisions about dynamics. Finally, with B-SVAR model, we still will be able to make meaningful assessments of model performance yet avoid overfitting our data.

The next section turns to an illustration of these virtues of B-SVAR modeling.

3 A B-SVAR Model of the American Political Economy

Modeling the connections between the economy and political opinions has been a major research agenda in American politics. A major contribution to this endeavor is the aggregate analysis of the economy and polity by Erikson, MacKuen, and Stimson (2002, chap. 10) (hereafter, EMS). EMS construct a recursive model where economic factors are used to predict political outcomes (e.g., presidential approval and macropartisanship). Their model illuminates linkages between key economic and political variables. The model built here is in the spirit of their work. We show how a B-SVAR model helps us cope with the four problems discussed above and thereby significantly enhances our ability to analyze American macro-political dynamics.[34]

3.1 *The Macro-political Economy in Terms of a Bayesian-SVAR Model*

We construct a nine-equation system that incorporates the major features of research about the U.S. macroeconomy and polity. We take as our starting point two parallel bodies of work: 1) the macropolity model of EMS and 2) the empirical macroeconomic models in Sims and Zha (1998) and Leeper, Sims, and Zha (1996) (hereafter abbreviated as SZ and LSZ, respectively). EMS create a large-scale dynamic model of the polity—how presidential performance, evaluations of the economy and partisanship are related to political choice. We build upon their models and measures to construct a model of the "political

[33]Of course, some may be opposed to the use of informed priors. But many researchers also are proponents of their use (Gill 2007; Garthwaite, Kadane, and O'Hagan 2005). As we have noted, the use of informed, elucidated priors now a standard practice in major branch of empirical macroeconomics.

[34]Chapter 10 of *The Macropolity* is a very serious modeling effort. The first part stresses (verbally) and presents schematically political-economic feedback and endogeneity. But the actual modeling—"historical simulation" —is mainly computational. To avoid the "nightmare of endogeneity," EMS use lags and impose a recursive structure on their system and then place coefficient values from their single-equation estimations into their equations one-by-one. EMS do not attempt to estimate their whole system of equations simultaneously and, as they themselves note, they do not provide any measures of precision for their impulse responses or forecasts. There is a report of an exogeneity test (123, fn. 8). But most of the identifying restrictions for EMS's model are posited, but not established through any analyses of the data.

sector'' of the macro-political economy. The political sector of the model consists of three equations: macropartisanship (MP), presidential approval (PA), and consumer sentiment (CS).[35] Since PA and CS are in large part the result of economic evaluations, the dynamics of the macroeconomy figure prominently in EMS's analysis. The feedback from these political variables to the economy connotes democratic accountability; it involves causal chains between economic and political variables. Thus, politics is both a *cause and a consequence* of economics.[36] To model the objective economic factors and policy that citizens evaluate, we utilize the empirical neo-Keynesian macroeconomic model of SZ and LSZ. We incorporate the economy by adding to the three variable political sector a common six-equation model frequently used by macroeconomic policy makers in the United States (*inter alia* Sims 1986a; Leeper, Sims, and Zha 1996; Sims and Zha 1998; Robertson and Tallman 2001). These six economic variables are grouped into four economic sectors. The first is *production* which consists of the unemployment rate (U), consumer prices (CPI), and real GDP (Y). The second and third are a *monetary policy* and *money supply* sectors consisting of the Federal funds rate (R) and monetary policy (aggregate M2). The fourth is an *information* or auction market sector that is the Commodity Research Bureau's price index for raw industrial commodities (Pcom).[37] The interest rate, approval, and MP variables are all expressed in proportions, whereas the other variables are in natural logarithms.[38] All the variables are monthly from January 1978 until June 2004.[39]

These nine endogenous variables—the six economic variables plus CS, PA, and MP—are modeled with a B-SVAR. Our model includes 13 lags. Our model also includes three exogenous covariates in *each* of the nine equations. The first is a dummy variable for presidential term changes, coded 1 in the first three months of a new president's term of office. The second is a presidential party variable that is coded -1 = Republican, 1 = Democrat. This variable allows us to account for the different effects of economics and politics across administrations. This achieves the same effect in our model as the ''mean centering'' of the CS and PA variables in Green, Palmquist, and Schickler (1998).[40] The final exogenous variable is an election counter that runs from 1 to 48 over

[35]PA and MP marginals are from Gallup surveys obtained from the Roper Center and iPoll; missing values for some months are linearly interpolated. CS is based on University of Michigan surveys as compiled in Federal Reserve Economic Data Base at the St Louis Federal Reserve Bank (http://research.stlouisfed.org/fred2/).

[36]See the concluding chapter of *The Macropolity*, especially pages 444–8. EMS quote the arguments of Alesina and Rosenthal (1995, 224) that ''the interconnections between politics and economics is sufficiently strong that the study of capitalist economies cannot be solely the study of market forces.'' EMS admit, however, that in most of their book they treat the economy as exogenous to the polity.

[37]Data on most economic variables and CS were obtained from the Federal Reserve Economic Data Base at the St Louis Federal Reserve Bank (http://research.stlouisfed.org/fred2/). All values are seasonally adjusted where applicable. The price index for raw commodities is from Commodity Research Bureau (http://www.crbtrader.com/crbindex/). The monthly real GDP series was generated using the Denton method to distribute the quarterly real GDP totals over the intervening months using monthly measures of industrial production, civilian employment, real retail sales, personal consumption expenditures, and the Institute of Supply Managers' index of manufacturing production as instruments (Leeper, Sims, and Zha 1996).

[38]The reason for these transformations is that our subsequent dynamic responses for the logged variables and the proportions (when multiplied by 100) will all be interpretable in percentage terms for each variable.

[39]Note that our sample differs from that used in EMS in two ways. First, we cover a more recent time span than that used in their analyses since we include data from 1978 to 2004. Second, we are working with monthly data, which means our analysis will contain more sampling variability than the aggregated quarterly data used by EMS to predict the relationships between unemployment, PA, and MP. We use monthly data because their arguments imply different reaction times for approval and MP to changes in the economy and CS.

[40]Including a signed dummy variable for party control in the model is equivalent to signing or estimating party-specific indicators of CS and PA in the model.

a four-year presidential term. It captures election cycle effects, as suggested by Williams (1990).[41]

There are two steps to specify a B-SVAR model of the U.S. political economy. The first is to identify the contemporaneous relationships among the variables. The second is to choose values for the hyperparameters that reflect generally accepted beliefs about the dynamics of the American political economy. Because the conclusions about political-economic dynamics may be due to these hyperparameters, we analyze the sensitivity of our results to these choices.

The structure of the contemporaneous relationships that we use—the identification of the A_0 matrix—is presented in Table 3. (The matrix A_+ allows for all variables to interact via lags.) The rows of the A_0 matrix represent the sectors or equations, and the columns are the innovations that contemporaneously enter each equation. The nonempty cells (marked with X's) are contemporaneous structural relationships to be estimated, whereas the empty cells are constrained to be zero.

We must provide a theoretical rationale for the contemporaneous restrictions and relationships. Beginning with the economic sectors, the restrictions for the Information, Monetary Policy, Money Supply, and Production sectors come from the aforementioned studies in macroeconomics. This specification of the structure of the economy has been found to be particularly useful in the study of economic policy (see e.g., Sims 1986b; Williams 1990; Robertson and Tallman 2001; Waggoner and Zha 2003a).[42] Next we ask, "which economic equations are affected contemporaneously by shocks to the political variables?" This is a question about the restrictions to the political shocks in the economic equations (the shocks in the three right-most columns and first six rows of Table 3). To allow for political accountability, contemporaneous effects are specified for political variables in two of the economic equations. First, the macropolity variables—PA, CS, and MP can have a contemporaneous effect on commodity prices.[43] This is consistent with recent results in international political economy such as Bernhard and Leblang (2006). Second, PA is expected to

Table 3 General framework for contemporaneous relationships in the U.S. political economy

Sector	*Variables*	*Pcom*	*M2*	*R*	*Y*	*CPI*	*U*	*CS*	*PA*	*MP*
Information	Pcom	X	X	X	X	X	X	X	X	X
Monetary policy	M2		X	X					X	
Money supply	R		X	X	X	X			X	
Production	Y				X					
Production	CPI				X	X				
Production	U				X	X	X			
Macropolity	CS				X	X	X	X		
Macropolity	PA				X	X	X	X	X	
Macropolity	MP				X	X	X	X	X	X

Note. The X's (empty cells) represent contemporaneous relationships to be estimated (restricted to zero) in the Bayesian SVAR model.

[41]The second dummy, for party control, may be weakly endogenous. Future research on the model will try to test for this possibility.

[42]The distinction between contemporaneous and lagged effects is conceived in terms of the speed of response. For example, consider shocks in interest rates. Commodity prices respond immediately to these shocks, whereas it takes at least a month for firms to adjust their spending to the rise in interest rates. Hence, there is a zero restriction for the impact of R on Y. Again, there is a lagged effect of R on Y and this is captured by A_+.

[43]We thank an earlier reviewer for suggesting the endogenous relationship between MP and the information sector.

have a contemporaneous effect on interest rates and on the reaction of the Federal Reserve (Beck 1987; Williams 1990, Morris 2000). The argument for estimating these structural parameters is that there can be a within-month reaction by the Federal Reserve to changes in the standing of the presidents who manage their approval. Finally, we ask "how do economic shocks contemporaneously affect the political variables?" This is a question about the structure of the last three rows of Table 3. We argue that the real economic variables—represented by GDP, unemployment, and inflation variables—contemporaneously affect the macropolity. The contemporaneous specification of A_0 for the macropolity variables (the last three rows of Table 3) allows all the production sector variables to contemporaneously affect the macropolity variables: innovations in GDP, unemployment, and prices have an immediate effect on CS, PA, and MP. These contemporaneous relationships are suggested by the control variables used in EMS and by related studies of the economic determinants of public opinion (*inter alia*, Clarke and Stewart 1995; Green, Palmquist, and Schickler 1998; Clarke, Ho and Stewart 2000). We also specify a recursive contemporaneous relationship among the CS, PA, and MP variables. This is suggested by the discussion of purging the economic effects from these variables in EMS (1998). The blank cells in Table 2 denote the absence of any contemporaneous impact of the column variables on the row variables. Finally, note that Σ has $(9 \times 10)/2 = 45$ free parameters and the A_0 matrix in Table 3 has 38 free parameters. Hence, it A_0 is overidentified.[44]

The second step in specifying the B-SVAR model is to represent the beliefs about the model's parameters. These beliefs are specified by the hyperparameters. EMS and SZ reveal similar beliefs about the character of the macro-political economy. SZ propose a benchmark prior for empirical macroeconomics with values of $\lambda_1 = 0.1$, $\lambda_3 = 1$, $\lambda_4 = 0.1$, $\lambda_5 = 0.07$, and $\mu_5 = \mu_6 = 5$. These values imply a model with relatively strong prior beliefs about unit roots, some cointegration, but with little drift in the variables. This prior corresponds to a political economy with strong stochastic trends and that is difference stationary. This is very similar to EMS's "running tally" model that also has stochastic trends but limited drift in the variables. EMS also reveal a belief that some variables in their political-economic system are cointegrated. Illustrative is EMS's argument that MP is integrated order 1. This reveals a belief the coefficients for the first own lags of some variables should be unity or that λ_1 is small. EMS also express confidence that PA and CS do not have unit roots, which is still possible with these beliefs. We denote this prior by the name "EMS-SZ Tight", or a *Tight* prior.

Because these hyperparameters are not directly elicited from EMS, it is wise to consider alternative representations of beliefs. A sensitivity analysis is recommended in an investigation like this (Gill 2004; Jackman 2004). We therefore propose additional prior specifications. This second prior, allows for more uncertainty than the EMS and SZ prior (larger SDs for the parameters and less weight on the sum of autoregressive coefficients and impact of the initial conditions). We denote this second prior, "EMS-SZ Loose" or *Loose*. The third prior is a Diffuse prior (but still proper, so that we can compute posterior densities for various quantities of interest). The hyperparameters for this final prior represents uninformative or diffuse beliefs about stochastic trends, stochastic drifts, and cointegration. The hyperparameters for this Diffuse prior allow for large variances around the posterior coefficients, relative to hyperparameters in the EMS-SZ priors. Thus, we analyze the fit of

[44]It is also possible to evaluate theoretically implied specifications of A_0. In the interest of brevity, we focus in this paper on the sensitivity of the results to the prior beliefs embodied in the hyperparameters. For examples with competing A_0 specifications, see Brandt, Colaresi, and Freeman (2008) and Sattler, Freeman, and Brandt (2008, 2009).

Table 4 Three B-SVAR priors and their posterior fit measures

Hyperparameter	*EMS-SZ Tight*	*EMS-SZ Loose*
Error covariance matrix scale (λ_0)	0.6	0.6
SD of A_1 (persistence) (λ_1)	0.1	0.15
Decay of lag variances (λ_3)	1	1
SD of intercept (λ_4)	0.1	0.15
SD of exogenous variables (λ_5)	0.07	0.07
Sum of autoregressive coefficients component(μ_5)	5	2
Correlation of coefficients/initial condition component (μ_6)	5	2
$\log(m(Y))$	4636	5482

a B-SVAR model with two informed priors and one uninformed prior. The two informative priors are summarized in the Table 4.

3.2 *Results*

Table 4 presents the log marginal data densities for the two informative priors. After evaluating the models on this criterion, we turn to the dynamic inferences. The interpretation of the B-SVAR model is dependent on the contemporaneous structure and the prior, but in a way made explicit by the Bayesian approach. We thus are able to show systematically how our results depend on the beliefs we bring to the B-SVAR modeling exercise.[45] As suggested earlier, the log marginal data density ($\log(m(Y))$) is used to compare the prior specifications.[46]

The final rows of Table 4 report the log marginal data density estimates. Loose prior model has the higher log marginal data density estimate.[47] The Loose prior generates a more likely posterior than the Tight prior based on the estimates of the log marginal data density. The log Bayes factor that compares the two prior specifications is 846, indicating a strong preference for the Loose prior over the Tight prior.

For the priors in Table 4, we computed the impulse responses for the full nine-equation system. The impulse responses for the two informed priors differ in a reasonable way. The responses to shocks in the Tight prior are more permanent and dissipate more slowly than those in the Loose prior, as expected. The latter allows for more variance in the parameters and more rapid lag decay (and thus faster equilibration to shocks than with the Tight prior).[48] The impulse responses for a Diffuse prior model have error bands that are very wide. Hence, interpretation of the magnitudes and direction of their dynamics is impossible (see the Appendix).

Based on the claims in EMS and conclusions in American political economy about the dynamics of the economy and polity, we focus on two sets of impulse responses for each prior.

[45]The additional sensitivity and robustness analysis will be made available with the replication materials for this article. These auxiliary results support the claims made here.

[46]All posterior fit results are for a posterior sample of 40,000 draws with a burnin of 4000 draws using two independent chains. The parameters in the two chains pass all standard diagnostic tests—traceplots show good mixing, Geweke diagnostics are insignificant, and Gelman-Rubin psrfs are 1. Therefore, we believe that the sampler has converged.

[47]A Diffuse prior will actually generate a larger log marginal data density value. But as footnote 32 noted, this will generate an incorrect inference about the models. First, inspection of the results from a Diffuse prior shows that it overfits the sample data, allowing many nonzero higher order lag coefficients. This means that impulse responses from this model have implausibly large confidence regions making any dynamic inferences difficult. The impulse responses for a Diffuse prior model (reported in the Appendix) have estimates that are not plausible.

[48]Space restrictions do not allow us to report the many impulse responses we produced. A full collection of them is available in the replication materials for this paper.

The first are the responses of the economy to changes in the macropolity variables. These allow us to evaluate political economists' claims about how the economy reacts to political and public opinion changes. The second set of responses are those of the macropolity equations (CS, PA, and MP) to shocks to the economy and polity. These allow us to evaluate EMS's claims (2002, p. 399ff.) about the impacts of unemployment shocks on PA and MP.

Figure 1 presents the subset of the responses of the economic equations to shocks in the macropolity sector variables.[49] Each row are the responses for the indicated equation for a shock in the column variable. Solid lines are used for the results for the Loose prior and dashed lines for the Tight prior. Responses are median estimates with 90% confidence region error bands, computed using an eigendecomposition method pointwise over a 48-month time horizon.[50] Since this is an SVAR model, we have to make a decision about the sign normalization of the shocks to each equation. In what follows we have used a likelihood-preserving normalization that maps the initial shocks to each equation to be positive (Waggoner and Zha 2003b).

The responses of the economy to shocks in the macropolity variables indicate that changes in public opinion and expectations do have predictable and sizeable effects on the economy. Shocks enter the commodity price (Pcom) equation positively, so that increases in CS lead to lagged decreases in commodity prices, reaching a maximum of nearly 1.3% over 30 months. Similarly, increases in approval generate less than 0.5% increases in commodity prices. Note that the differences between the Loose and the Tight priors are mainly about the speed with which the system equilibrates (with a major exception to be noted).

With respect to the monetary policy and money supply sectors (R and M2), changes in CS and PA affect interest rates and monetary policy. In the Loose prior model, increases in CS lead to lower interest rates (a drop of over 20 basis points that equilibrates back toward zero). A similar, more permanent interest rate reaction is seen in the results for the Tight prior model (the dashed lines).

The problem with the Tight prior model is in the responses of M2, the nominal money supply, to CS shocks.[51] This response should be positive, since as the public expects a stronger economy, the money supply should expand since there will be inflationary pressures on credit. This is what we see for the Loose prior model which produces a nearly 2% expansion in M2 and then a delayed response in inflation (i.e., the CPI response to CS shocks). The Tight prior model response of M2 to CS shocks is incorrect, since more consumer optimism about the economy leads to a nominal contraction of the money supply at the same time interest rates would be expected to fall. This is because the Tight prior model tightly constrains the relationship between nominal and real money balances in the economy. Consequently, consumers misperceive the relationship between real and nominal money balances. This is inconsistent with real inflation adjustment between the money supply and inflation. Thus, there is an anomalous response for M2 to CS shocks produced by the Tight prior model (compare the solid to the dashed lines for this shock-response).

[49]These responses were generated using the Gibbs sampler for B-SVAR model in Waggoner and Zha (2003a). This Gibbs sampler draws samples from the posterior distribution of the restricted (overidentified) A_0 matrix and then from the autoregressive parameters of the model. These draws are then used to construct the impulse responses (Brandt and Freeman 2006). The responses have been scaled by a factor of 100, so they are in percentage point terms. We employ a posterior based on 20,000 draws after a burnin of 2000 draws. Similar results were obtained for a posterior sample twice as large using two independent Markov Chain Monte Carlo (MCMC) chains.

[50]Discussion and examples of why this is a preferable confidence region can be found in Brandt and Freeman (2006).

[51]We are indebted to Chetan Dave for his help in understanding this result.

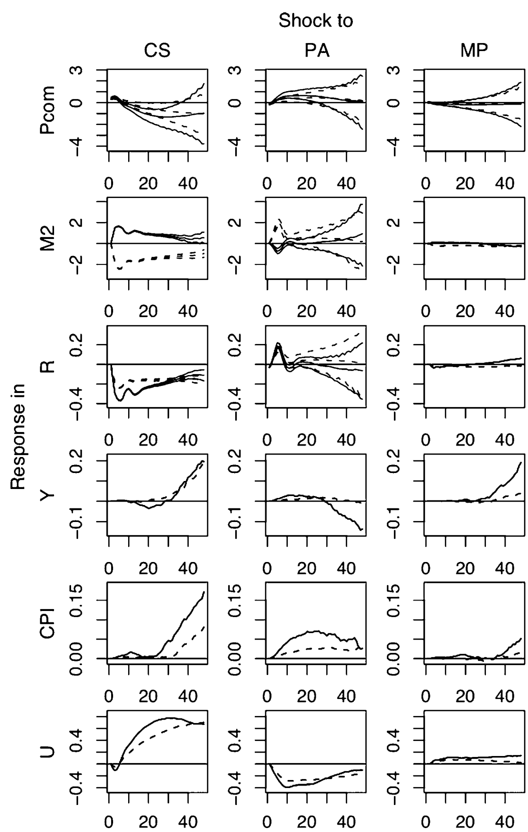

Fig. 1 Impulse responses of the economic sectors to political shocks over 48 months. Responses are median responses computed from the B-SVAR posterior. Error bands are 90% regions around the median response. Solid lines are used for the median responses and error bands for the Loose prior model; dashed lines are used for the Tight prior model. Shocks to the (row) equations are positive 1 SD innovations in the column variables. See the text for discussion and interpretation.

For both models, PA shocks generate brief increases in interest rates (R) that lasts about 10 months. In contrast, positive shocks in PA generate different responses in M2. The response of M2 produced by the Tight prior model only makes sense if there is public misperception of real versus nominal money. This is because rising PA is normally tied to a strong economy. If voters misperceive the real versus the nominal amount of money in the economy, then PA shocks will lead (incorrectly) to increases in the money supply.

It is important to note that the interest rate and money responses for the Loose prior model are consistent with political monetary cycle arguments that presidents attempt to manage their approval by strengthening the economy; the Fed works counter-cyclically to reduce inflation and unemployment both of which also move in the expected directions to approval shocks (Beck 1987; Williams 1990). These responses are consistent with the idea of political accountability where policy responds to public perceptions of the president. The Tight prior model's impulse responses do not support this interpretation. This is likely because the Tight prior model's strong emphasis on unit roots leads the trends in R and M2 to dominate the impulse response rather than allowing the influence of short-term cyclical factors like CS and PA shocks to play a role in the American political economy. This is likely since the general direction of inflation and interest rates is downward in our 1978–2004 sample.

For the production sectors—real GDP (Y), inflation (CPI), and unemployment (U)—the political shocks also generate responses. Real GDP responds to political shocks, albeit with a very long lag (over 30 months). This response is more pronounced for the Loose prior model. For both models, positive shocks in CS and PA lead to higher inflation (CPI). Note though that these responses are small—always less than 0.2%. The median total response of CPI to the CS and PA innovations over 48 months is less than 0.2%.[52] The positive shocks to the unemployment equation, or increases in CS increase unemployment by at most 0.7% with a lag over 48 months. For both models, shocks to PA lower unemployment, by about a 0.4 points around 10 months and then declining to zero at 48 months. These are possibly some expectational responses as both variables are trending. Thus, even the non-zero effects of the macropolity on the real economy are weak. The key conclusion here is that political economists' claims about the endogeneity of policy and outcomes to public opinion are borne out by an analysis of the entire system of equations. When we use the Tight prior with a strong emphasis on unit roots and cointegration, we see reactions that generally repeat the trends in the data. When we use the Loose prior that puts more weight on short-term cyclical forces, one sees policy reactions to changes in CS and PA.

The other side of the B-SVAR system are the impacts of the economy on the macropolity. Evaluating and quantifying the impacts of economic shocks on PA and MP is a central part of EMS's project (2002, chap. 10). EMS examined the effect of an unemployment shock in 1959 on Eisenhower's approval and subsequently on MP. Here we study the general reaction of PA and MP to a one SD shock in unemployment. We trace out the impacts in a full, nonrecursive system that includes both an economy and a polity.[53]

Figure 2 present the impulse responses for the macropolity equations. We can use these to judge the relative impacts of different economic shocks, like unemployment and inflation innovations, on CS, PA, and MP. Each plot in the figure is the impact of a positive one SD change in the column variable to the row equation. Again, we use 90% posterior confidence regions computed via eigendecomposition methods, with solid lines for the responses for the Loose prior model and dashed lines for the responses of the Tight prior model.

These responses allow for the most direct comparison of our B-SVAR methods to those of EMS. EMS focus specifically on the impact of a one-point increases in unemployment (that decays by 0.9 per month) on PA and MP. They find (200, 399) that such a shock lowered (Eisenhower's) approval by about 2 points and permanently increased MP (which is the Democrat's share of the two-party identification), by fractions of a point. EMS's analysis assumes that relationships are recursive and nonsimultaneous. Also they provide no error bands for their impulse responses. Our models are simultaneous equation models of the American political economy, and we provide measures of uncertainty for our impulse responses.

The impulse responses in Fig. 2 present a very different set of conclusions to those reported in EMS. Column 6 of the graphs in Fig. 2 gives the responses of CS, PA, and

[52]This median total impulse response is found by cumulating the MCMC sample of each impulse response and then summarizing its median and credible interval.

[53]Recall that EMS's model does not have an economy. For instance, their model in chapter 10 has no Phillips curve. Rather EMS create unemployment and inflation variables by running independent regressions with dummies for the identities of the partisan identities of incumbents.

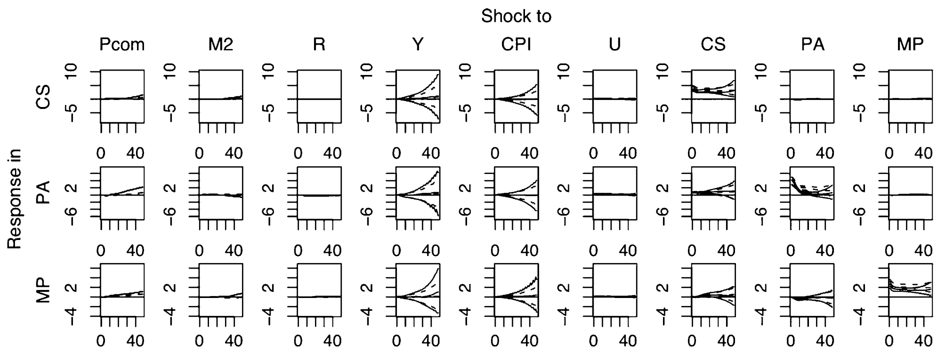

Fig. 2 Impulse responses of the macropolity sectors to economic shocks over 48 months. Responses are median responses computed from the B-SVAR posterior. Error bands are 90% regions around the median response. Solid lines are used for the median responses and error bands for the Loose prior model; dashed lines are used for the Tight prior model. Shocks to the (row) equations are positive 1 SD innovations in the column variables. See the text for discussion and interpretation.

MP to a 1 SD (approximately 0.16 monthly) shock in unemployment (U).[54] So what do we learn from our shock to unemployment? First, relative to the other economic variables in the model, there is *no meaningful response* in CS, PA, or MP to a shock in unemployment. CS rises at most 0.22 points in the first period (Loose prior model 90% credible region [0.16, 0.31]) after such as shock, PA's maximum response is 0.29 points, and MP's maximum response is 0.12 points. All the PA and MP responses to unemployment shocks have error bands that include zero before the entire 48 months (19 months for CS, 30 months for PA, and 22 months for MP). At 48 months, the responses of PA and MP to unemployment shocks are always less than 0.06 percentage points (for either prior) (thus why they appear non-existent on in Fig. 2). This is in direct contrast to the results that EMS (p. 401) report; they find a maximum 2–3 point response in PA and a subsequent small response (less than a full point) in MP—both in less than a year.

Accounting for the endogeneity of CS, PA, and MP, we do not find any recursive causal linkage in the last three columns of Fig. 2. Instead, the results for our model (for both priors) shows that CS, PA, and MP respond most strongly to their own innovations. The responses of these equations to shocks in the economy are either weak or have large error bands (contrast the effects of the Pcom shocks and of the real GDP and inflation [CPI] shocks to those in the final three columns of the figure).

Commodity prices, CS and PA's own innovations have the largest impact on PA responses. A 1 SD (an initial quarter percent) shock to commodity prices increases PA by 2 points over 48 months. Thus, information markets have a degree of influence on both CS and PA.

[54]The results for the Loose prior model indicates that it takes *seven months* after a 1 SD shock to monthly unemployment to generate a total of a one point response. This shock to unemployment thus is historically consistent with the (1978–2004) sample we used here. Alternatively, one could ask, in favor the EMS analysis, how long in monthly terms does it take to get a 0.33 point shock to unemployment (thus translating their quarterly shock back into months)? Based on our models, the answer is two months (where the cumulative impact would be a 0.32 point increase in unemployment). So whichever way one considers the shock, our 1 SD shock is more realistic and historically accurate than the quarterly one point shock considered by EMS.

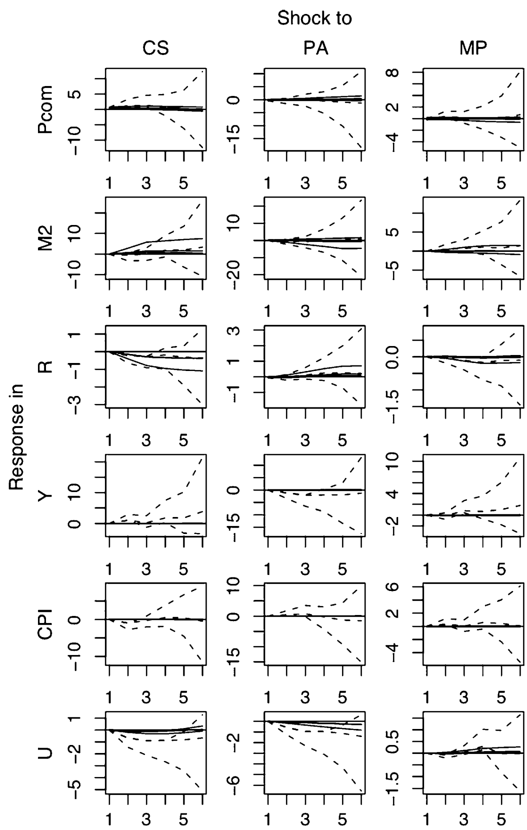

Fig. 3 Impulse responses of the economic sectors to political shocks over six months. Responses are median responses computed from the B-SVAR posterior. Error bands are 90% intervals around the median response. Solid lines are used for the median responses and error bands for the Loose prior model; dashed lines are used for the Diffuse prior model. Shocks to the (row) equations are positive 1 SD innovations in the column variables. Note that the responses are in percentage point terms over *six* months, meaning that the Diffuse prior results have error bands that are much too large to be plausible.

The effect of CS shocks on PA reflects this influence as well. The initial median impact of a shock to CS on approval is 0.68 points for both models. Note that this is more than two times larger than impact of an unemployment shock on PA *and CS shows little to no response to the shock in unemployment*. Thus, innovations in information markets (Pcom) impact CS (here, expectations about the future economy) and PA and then the impacts on CS feed-forward into subsequent PA changes. Note, however, that the real economy does not have sizeable impacts on any of the macropolity variables.

Consider next the responses of the macropolity sector. These results differ from those previously seen in the literature (cf., EMS, Chapter 10) because they are the result of embedding the macropolity in a full model of the political economy. CS responds mainly to its own shocks and not those of the other political variables (not even with a lag). Neither CS nor approval responds meaningfully to changes in MP.

One of the main questions for both our analysis and for EMS is the exploration of what moves aggregate MP? The final row of plots in Fig. 2 shows the responses for the MP

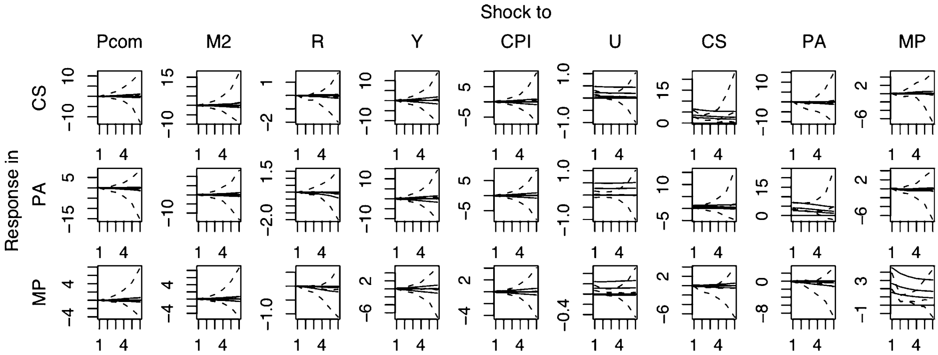

Fig. 4 Impulse responses of the macropolity sectors to economic shocks over six months. Responses are median responses computed from the B-SVAR posterior. Error bands are 90% intervals around the median response. Solid lines are used for the median responses and error bands for the Loose prior model; dashed lines are used for the Diffuse prior model. Shocks to the (row) equations are positive 1 SD innovations in the column variables. Note that the responses are in percentage point terms over *six* months, meaning that the Diffuse prior results have error bands that are much too large to be plausible.

equation. Positive shocks in the production sector and in PA have no sizeable or lasting impact on aggregate partisanship (*contra* EMS). The MP responses to CS and PA shocks are always less than 0.25 points. Initially, the responses are negative, and then turn positive. In the end, the MP equation is mainly driven by shocks to MP itself.

4 Conclusion

Political scientists need to learn how to specify B-SVAR models. Translating beliefs into the contemporaneous relationships in A_0 appears straightforward. Careful study of the literature on topics like MP usually reveals how researchers conceive some of these relationships. Admittedly, scholars often do not mention some contemporaneous relationships, and it is not clear that setting them to zero is reasonable. But the virtue of the structural VAR approach is that it allows us to estimate whether the respective contemporaneous coefficient should be unrestricted. Using a Bayesian approach also allows us to summarize our uncertainty about such contemporaneous restrictions. In addition, we need to learn how to specify the hyperparameters. Scholars sometimes are not clear about their beliefs about all these parameters. How much sampling error should be discounted via the choice of λ_0 is another issue. In recent years, political methodologists have produced a number of useful findings about the persistence properties of political data. However, macroeconomists are far ahead of us in this regard. They have much more experience in translating their arguments and experience in fitting B-SVAR models into clusters of hyperparameters. An important part of this experience comes from years of attempting to forecast the macroeconomy. The efforts to forecast the macropolity and international relations are, for myriad reasons, less well developed in our discipline.[55]

[55]Perhaps this is why most Bayesians in political science employ uninformed priors. On this point, see Brandt and Freeman (2006).

Important extensions of the B-SVAR model are being developed. For example, there are new methods for translating theory into additional restrictions on the effects of lagged endogenous variables (the A_+ matrix in the model) and for formally testing these restrictions (e.g., Cushman and Zha 1997). Some researchers contend that formal models produce more useful structural insights than VAR models (structural, RF and/or Bayesian). Proponents of Bayesian time series models reply that formal models often suffer from problems of observational equivalence and that they are very difficult to fit to data. A more catholic approach is taken by Sims (2005) who argues that formal models—in the case of macroeconomics, Dynamic Stochastic General Equilibrium (DSGE) models—are good for ‘‘spinning stories’’ and that these stories ought to be restrained or refined by the results of VARs. Work is underway in macroeconomics to try to make this connection more explicit. This work specifically uses DSGE models to develop informed priors for B-SVAR models. The DSGE models are linearized at the point representing general, macroeconomic equilibrium and then the parameter values from the DSGE model are translated into the hyperparameters of the B-SVAR model.[56]

In political science, we lack a well-developed, general equilibrium theory of the kind that spawned DSGE models. However, spatial theory and the new works on electoral coordination and campaign finance (Mebane 2000; Mebane 2003; Mebane 2005) point the way to the development of such theory. The challenge is to join these works with the B-SVAR approach to make more sustained progress in the study of the macropolity.[57]

Funding

National Science Foundation (grant numbers SES-0351179 to J.R.F., SES-0351205 and SES-0540816 to P.T.B.).

Appendix: Impulse Responses for Diffuse Prior Model

This appendix contains the impulse responses for the models with the Loose and Diffuse priors. Figures 3 and 4 plot these responses over *six* months, rather than *forty-eight* months as in Figs. 1 and 2, to illustrate the explosive nature of the Diffuse prior responses relative to the Loose prior responses. Using the longer time span would make it impossible to see the Loose prior responses because of the large scale of the Diffuse prior responses. Note that the six-month impulse response function results for the Diffuse prior have error bands that are large and implausible given the historical values of U.S. macroeconomic and political data.

[56] Ingram and Whiteman (1994) and Del Negro and Schorfheide (2004) draw informed priors from DSGEs for BVARs. Leeper et al. (1996) argue that DSGE models provide insights into the long-term economic dynamics and VARs into the short-term dynamics of the economy. In a more recent article, Sims (2005) notes that DSGE models are better than VARs for ‘‘spinning elaborate stories about how the economy works’’ but expresses some skepticism about whether linearizations of DSGE models usually produce accurate second-order approximations to the likelihood. He goes on to say, ‘‘No one is thinking about the time varying residual variances when they specify or calibrate these [DSGE] models.’’ Sims predicts a ‘‘hornet’s nest’’ for macroeconomic DSGE policy modelers.

[57] For a sketch of how this development might occur, see Freeman (2005).

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