Modeling Macro-Political Dynamics*

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Abstract

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 Erikson, MacKuen and Stimson's model of the American macropolity (2002) with those of a leading macroeconomic model of U.S. (Sims and Zha 1998 and Leeper, Sims, and Zha 1996). This structural model, with a loose informed prior, yields the best performance in terms of a mean squared error loss criterion and new insights into the dynamics of the American political economy. The model 1) captures the conventional wisdom 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 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.

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1 Introduction

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

Modeling macro-political dynamics in these varied research areas is complex for four reasons. The first is the problem of *scale*. Macro-political systems are composed of many variables and of multiple causal relationships. For instance, in American political economy one must take into account relationships between public opinion variables and partisanship, and between these variables and output, employment, and prices. Similarly, students of international relations must account for the behavioral relationships of all important belligerent groups within and between countries.

A second problem is *endogeneity*. While some variables in macro-political processes clearly are exogenous, we believe that other variables are both a cause *and* a consequence of economic processes. 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). If we have genuine political economy models, macroeconomic theory predicts endogeneity between variables like inflation and unemployment.

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

Finally, *specification uncertainty* is a problem. We have no equivalent of macroeconomic 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 also tend to "overfit" our data.

None of the approaches commonly used to model dynamic processes in political science addresses all four problems together. The most common macro models are single equation autoregressive distributed lag models (ADL) and pooled time series cross-sectional (TSCS) regressions. Both of these single equation models expressly omit multiple relationships between endogenous variables. The common practice is to make each relationship the subject of a different article, to treat a variable as dependent in one article and independent in another.[1] The problem of endogeneity usually is acknowledged by users of ADL and TSCS models, but rarely are exogeneity tests performed. 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 they rarely evaluate the adequacy of their instruments. In addition, treatments of persistence often are based on knife-edged pretests for unit roots.[2]

Reduced form [RFs] representations of simultaneous equation models address these scale and endogeneity issues. Some users of RFs in comparative political economy analyze models with 3–4 variables (equations) in which all variables are treated as endogenous. The problem is that most macroeconomists now argue 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 student of international political economy who has built a reduced form model on this scale, for instance, a model that includes 3–4 equations for *each* of three or four trading partners.[3] Students of international conflict have built reduced form models with 24–28 equations, but they 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

[1]For a recent review of ADL and single equation models see De Boef and Keele (2006).

[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, Franzese and Hays have not yet attempted to analyze fuller conceptions of endogeneity in macro-political processes.

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

the specification uncertainty will render the dynamic responses quite imprecise.[4]

Finally, users of simulation methods such as Erikson, MacKuen and Stimson (2002, Chapter 10) and Alesina, Londregan and Rosenthal (1993, 24-25) address the scale and persistence issues. But they expressly eschew endogeneity, making heroic restrictions that treat macro-political processes as (quasi-)recursive. These researchers also do not produce meaningful measures of precision for their dynamic analyses.[5]

Our discussion is divided into two parts. Part one introduces a Bayesian structural time series model and explains how this model addresses the problems of scale, endogeneity, persistence and specification uncertainty. 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 Erikson, MacKuen and Stimson's (2002, Chapter 10) model of the American macropolity with those of a leading macroeconomic model of U.S. (Leeper, Sims and Zha 1996, Sims and Zha 1998). This structural model, with a loose informed prior, yields the best performance in terms of a mean squared error loss criterion and new insights into the dynamics of the American political economy. The model 1) captures the conventional wisdom 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 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. In the spirit of the Bayesian approach (Gill 2002, 2004; Jackman 2004, in progress),, these results are insensitive to alternative specifications of prior be-

[4]Examples of these larger scale reduced form models in international relations are Goldstein and Pevehouse (1997), Pevehouse and Goldstein (1999), and Goldstein, Pevehouse, Gerner and Telhami (2001).

[5]For example, in their simulation chapter, Erikson et al. refer to endogeneity as a "nuisance" and a "nightmare" (2002, 386). 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 et al. also provide no error bands for their impulse responses.

liefs, including beliefs motivated by the 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's (1980) seminal article on macroeconomic modeling, political scientists began exploring the usefulness of reduced form methods (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 our equations. Macro theory is at best a set of loose causal claims which translate into a weak set of model restrictions. In this view, progress in macro theory results from analyzing reduced forms and subjecting these forms to (orthogonalized) shocks in the respective variables (e.g., "innovation accounting"). If there are any structural insights they are best represented as contemporaneous relationships between our variables, but then only as zero restrictions (Bernanke 1986). In the last twenty 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 our discipline is the rise of the Bayesian approach to data analysis. Philosophically, it rests on two main premises: a) political phenomena are inherently uncertain and changing and b) available prior information should be used in model specification (Gill 2004, 324). Bayesianism stresses systematically incorporating previous knowledge about a subject 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 the model's assumptions (*ibid.* 333–334). Bayesian analyses involves such things a summarizing the posterior distributions for models rather than performing familiar, frequentist hypothesis tests. While in some cases (asymptotically) the results of frequentist and Bayesian approaches may be equivalent, they represent different stances on how modeling ought to proceed.[6]

Here we bring these two developments together. We show how the Bayesian approach makes reduced form time series analysis both more systematic and informative. We also point out the distinctiveness of Bayesian time series analysis. For example in the presence of nonstationarity, Bayesian and frequentist time series inference can be asymptotically quite different.

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 on the system of equations.[7] The structure of the system—particularly its contemporaneous relationships—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.

Our basic model 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 of the endogenous variables in the system. This produces a dynamic simultaneous equation model that can be written in matrix notation as

$$\underset{1\times m}{y_t}\,\underset{m\times m}{A_0} + \sum_{\ell=1}^{p} \underset{1\times m}{y_{t-\ell}}\,\underset{m\times m}{A_\ell} = \underset{1\times m}{d} + \underset{1\times m}{\epsilon_t}, \quad t = 1, 2, \ldots, T, \tag{1}$$

with each vector's and matrix's dimensions noted below the matrix. This is an m-dimensional

[6]Gill (2004, 333-334) 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. See Jackman (2004) explains how the two approaches differ but also how, under certain conditions, the frequentist and Bayesian 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, 327–328.

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

vector autoregression (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 ℓ^{th} 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

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

Equation (1) is a structural vector autoregression 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). 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 non-singular and subject only to linear restrictions.[8] Zero restrictions on elements of A_0 imply that the respective variables are unrelated contemporaneously.

The estimation of this model can be achieved via multivariate regression methods, as detailed in Sims and Zha (1998) and Waggoner and Zha (2003*a*). 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 that for A_0.[9] To describe the prior for the parameters, we place the corre-

[8]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.

[9]This prior is a revised version of the earlier "Litterman" or "Minnesota" prior for reduced form VAR models (Brandt and Freeman 2006, Doan, Litterman and Sims 1984, Litterman 1980). Doan et al. originally referred to the Minnesota prior as a "standardized prior" or "empirical prior" (1984:2, 4, respectively). 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 macroeconomists 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).

sponding elements of the prior for 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 all the parameters, $\pi(a)$ is then,

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

where the tilde denotes the mean parameters in the prior for a_+, $\phi(\cdot,\cdot)$ is a multivariate normal distribution, and Ψ is the prior covariance matrix for $\tilde{a}_+$.[10]

Sims and Zha's (1998) prior addresses the main problems of macro modeling. For example, the prior addresses the scale problem by putting lower probability on the coefficients of the lagged effects. But rather than imposing (possibly incorrect) exact restrictions on these coefficients such as 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 on the model coefficients is then correlated across equations in a way that depends on the contemporaneous relationships between variables (the covariance of reduced form disturbances via the A_0 matrix of the SVAR). This allows beliefs about the identification of systems such as the 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.[11]

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

[10] 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).

[11] 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.

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 around the first lag coefficients are proportionate to those for the coefficients of all other lags.

2. The weight of each variable's own lags in explaining the its variance is the same as the weights on other variables' lags in an equation.

3. The standard deviation 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 standard deviation of the intercept is proportionate to the standard deviation of the residuals for the equation.[12]

A series of hyperparameters are used to scale the standard deviation of the model coefficients to reflect these beliefs. Table 1 summarizes the hyperparameters in the Sims-Zha prior. 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 reduced form contemporaneous residuals. If for theoretical reasons we expect large correlations in the reduced form innovations of two variables, the corresponding regressors are similarly correlated to reflect this belief and to ensure that the series move in a way that is consistent with their unconditional correlations.[13]

[Table 1 about here.]

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

[13]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."

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

$$Pr(A_0, A_\ell, \ell = 1, \ldots, p) \propto \phi(a_+ a_0 | Y)\phi(\widetilde{a_+}, \Psi)\pi(a_0) \quad (3)$$

Estimation and sampling from the posterior of this model is via a Gibbs sampler (detailed in the appendix). The main complication in the Gibbs sampler is the sampling from the over-identified cases of the contemporaneous A_0 coefficients. Waggoner and Zha (2003*a*) 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.[14]

A key feature of the B-SVAR model is that its contemporaneous restrictions affect the dynamic parameters. This can be seen by examining the reduced form of the structural model in equation (1). The reduced form 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,

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

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 ℓ^{th} lag, and p the maximum number of lags. Note that in this formulation, all of the contemporaneous effects (which are in the A_0 matrix of the SVAR) are included in the covariance of the reduced form residuals, u_t.

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

[14]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 the Gibbs sampler.

equation parameters via

$$c = dA_0^{-1} \quad B_\ell = -A_\ell A_0^{-1}, \quad \ell = 1, 2, \ldots, p, \quad u_t = \epsilon_t A_0^{-1} \tag{5}$$

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

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

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

In a standard reduced form 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 reduced form parameters of the model and from these parameters the elements of the associated A_0 can be ascertained.[15]

For SVARs, the A_0 is typically non-recursive and over-identified. Frequentist estimation use a maximum likelihood procedure to estimate the non-recursive contemporaneous relationships in the parameters of A_0 (Blanchard and Quah 1989, Bernanke 1986, Sims 1986*b*). This procedure uses the reduced form residual covariance Σ in equation (6) to obtain estimates of the elements of A_0. In either frequentist or Bayesian approaches to estimation, the reduced form 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,

[15]The reduced form 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 reduced form 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).

more than $[m \times (m+1)]/2$ zero restrictions, are called over-identified.[16]

Non-recursive 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 reduced form 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 reduced form 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 reduced form residual u_s at time $s > t$. These impulse responses are computed recursively from the reduced form coefficients and A_0:

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

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

The interpretation of the impulse responses for SVAR models can differ those of more reduced form VAR models. In the latter one employs a Cholesky decomposition of the Σ matrix which is a just identified, recursive model. In turn all the shocks hitting the system in the innovation accounting have the same (positive) sign. In SVAR models, the signs of the shocks can vary across equations. The signs of the shocks hitting each equation in an SVAR model can be negative or positive depending on the pattern of the correlation residuals for each equation. In a non-recursive

[16]To estimate non-recursive 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.

system the contemporaneous shocks to a set of equations may be negatively (or positively) correlated with each another so shocks with different signs may enter each equation. For instance, positive shocks hitting one equation may imply negative shocks hit other equations. The so-called "sign normalization" complicates the interpretation of the respective impulse responses.[17]

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: autoregressive distributed lag models, error correction models, ARIMA models, reduced form 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.

2.2.1 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.[18] 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 equate to at least 237 parameters). The flexibility of the model comes at a cost: higher degrees of parameter uncertainty relative to the available degrees of freedom.[19]

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

[17] For discussion of sign normalization see Waggoner and Zha (2003*a*). This problem 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 2006).

[18] 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).

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

large, unrestricted models tend to overfit data. For example, they attribute too much impact to the parameters on distant lags.[20] 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).

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).

2.2.2 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 Erikson et al.'s work on the American macropolity (2002: Chapter 10) an entire, recursive equation systems is assumed.[21]

The deeper problem here is that of identification or structure. In the case of *macro*-political analysis this problem is especially severe because we usually work in non-experimental settings. Manipulation of variables and experimental controls are not possible. Manski (1995, 3) emphasizes the seriousness of this problem: "…the study of identification comes first. Negative identification

[20]Sampling error is one of the reasons too much emphasis is put on the data at distant lags. On the problems associated with increases in model scale relative to the dynamic analysis and forecasting see Zha (1998), Sims and Zha (1998, 958–960) and Robertson and Tallman (1999, esp., p. 6 and fn. 7).

[21]Erikson et al. 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 first illustration.

findings imply that statistical inference is fruitless. . . .” Manski acknowledges endogeneity as one of three effects that make identification difficult.[22]

While (Bayesian) SVAR models allow all variables to be endogenous, users of them still encounter identification problems. The most well known of these is the Lucas critique. This critique holds that these models cannot be used for policy analysis: the public will anticipate policies and thereby nullify those policies’ effects. Analysts who want to use B-SVAR models to study the effects of U.S. foreign policy interventions would be thwarted by belligerents’ expectations of these interventions, expectations that reduce any impact the interventions might have on conflicts. In refuting this critique, macroeconomists invoke *politics*. If policies were optimal and agents had perfect (exactly the same) information as policy makers, policy evaluation would be difficult to perform. Because of politics, policy is not optimal and agents are not perfectly informed. Politics produces enough “autonomous variation in policy”—the source of which agents cannot discern—that we can identify multi-equation time series models and use them to study the consequences of policy innovations and counterfactuals (Sims 1987). In this sense, *politics aids identification*.[23]

For political scientists this argument has normative significance. Endogeneity often is synonymous with political accountability. The political uncertainty on which macroeconomists rely for identification is from our point of view a source of democratic legitimacy. Allowing for endogeneity between popular evaluations of government, policies, and policy outcomes is essential to capture the essence of democratic politics.

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 contem-

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

[23]Sims (1987, 298) writes “. . . actual policy always contains an unpredictable element from this source [politics]. The public has no way of distinguishing an error by one of the political groups choosing its target policy from a random disturbance in policy from the political process. Hence members of such a group can accurately project the effects of various policy settings they might aim for by using historically observed reactions to random shifts in policy induced by the political process.” See also Cooley, LeRoy and Raymon (1984) and Granger (1999). The idea is that Bayesian SVAR models have embedded in them reaction functions and mechanisms by which agents form expectations. These functions and reactions are not made explicit or separated out from the other dynamics. But these functions and mechanisms are assumed to be present in the data generating process (Sims 1987, 307; Zha 1998, 19; Leeper, Sims and Zha 1996, 10ff.).

poraneous relationships are estimated. The real advantages of this modeling approach are 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 (for an example of this, see Williams (1990)). Some of the variables are likely to be contemporaneously related—e.g., 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 thought to be 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 over-identified and non-recursive nature of the A_0 matrix create challenges in estimation and interpretation of the model.[24]

[24]The idea that theories imply restrictions on contemporaneous relationships may seem new. But Leeper, Sims and Zha (1996, 9ff.) point out 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 A_0 forces the respective posterior mode to be zero.

2.2.3 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, DeBoef and Granato 1997, Clarke, Ho and Stewart 2000). Erikson et al. (1998, 2002, Chapter 4) make a sophisticated argument about the interpretation of macropartisanship as a nonstationary "running tally of events." Such arguments reveal 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 / non-stationarity 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 standard deviation 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.[25] The prior allows analysts to incorporate beliefs about stochastic trends and cointegration. Continuing with the enumeration in Table 1, 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:

[25] 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.

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 prior 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.

Values of zero for each of these parameters implies 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 dummies represent stochastic restrictions on the coefficients consistent with the mixed estimation method of Theil (1963). As $\mu_5 \rightarrow \infty$, the model becomes equivalent to one where the endogenous variables are best described in terms of their first differences and there is no conintegration. 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 $\mu_6 \rightarrow \infty$ 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 in the prior 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 the prior hyperparameters. Second, claims about near- and fractional integration can be expressed in terms of μ_5 and μ_6. Using these two additional priors should enhance the performance of macro-political models, especially of models of the macro-political economy.[26] 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.[27]

2.2.4 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 variables in the model and their 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.

Observational equivalence (*viz.*, poor identification) is consequence of both forms of uncertainty, 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-

[26] 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 VARs with exact restrictions.

[27] From the Bayesian perspective nonstationarity is not a nuisance. Williams (1993) and Freeman, Williams, Houser and Kellstedt (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).

15; Sims and Zha 1998, 958-960). 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).[28]

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, and A_0 identification choices). Second, there are a large variety of possible *prior beliefs* for BVAR and B-SVAR models (for more details on this point, see Ni and Sun 2003, 2004, 2005).

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 existing Bayesian VAR literature proposes four different measures for comparing model specification and fit (Sargent, Williams and Zha 2006, Sims and Zha 2006). These are 1) the log posterior density (LPD = the log likelihood plus the log prior), 2) marginal data densities (MDD or marginal likelihoods) which can be used to compute Bayes factors, 3) Bayes factors (BF) which compare the posterior probabilities of the models under various specifications, and 4) Bayesian information criteria (BIC or Schwarz criteria) which adjust the posterior probability by a penalty

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

for the number of parameters.[29]

The evaluation of competing *prior* specifications or beliefs, requires comparing different priors and their impacts on posterior distribution 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. While 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 cannot use Bayes factors to compare priors because they themselves are sensitive to the prior specification (Kass and Vaidyanathan 1992).

Several possibilities for comparing different priors for the same model do exist in the literature. The include comparisons of the 1) loss functions (e.g., mean squared error) for the parameters and 2) loss functions of quantities of interest (e.g., impulse responses, decompositions of forecast error variance, marginal data densities) (Ni and Sun 2003, 2004, 2005). The comparison of loss functions for these quantities under different priors is most useful when evaluating the properties of known parameter values (i.e., simulation experiments). The comparison of loss functions for quantities of interest is more relevant for comparing priors for a model with unknown parameters. In the latter, for each prior specification, one computes the loss function value for the quantities of interest and then compares these across different priors. In many cases, this is a complex calculation since it involves either working with Monte Carlo samples or non-linear functions of the posterior (e.g., impulse responses).

One common suggestion by non-Bayesians is to "estimate" the prior hyperparameters. That is, one should treat the prior 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, 31–32) 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

[29] Sims and Zha and later Sargent, Williams and Zha use the LPD to compute the BIC on the grounds that is accounts for both the uncertainty of the likelihood and the prior—typically one uses just the likelihood instead of the LPD.

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 (1993, 231) argues that “Classical inference is ... based on inferring something about a population from a sample of data. In time-series, the sample is not random, and the population contains the future as well as past.” The presence of unit roots and the special nature of a time series sample thus 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.

To comparing prior specifications in a B-SVAR model, we follow Ni and Sun (2003, 2004, 2005) who evaluate priors in both Monte Carlo studies and real data examples of BVARs. They show that one can compare priors in a model with actual data using a loss function (such as mean squared error) for the quantities of interest. We prefer a measure of the loss around mode of the posterior of the marginal data density. The reason for this is that it summarizes uncertainty about both the parameters and in-sample fit. The log marginal data density (know also as the log marginal likelihood) for the B-SVAR model is given by

$$log(MDD) \quad = \quad logL(Y|A_0 A_+) + logPr(A_0, A_+) - logPr(A_0, A_+|Y) \tag{8}$$

where $logL(Y|A_0, A_+)$ is the log likelihood for the B-SVAR model, $logPr(A_0, A_+)$ is the log prior probability of the parameters, and $logPr(A_0, A_+|Y)$ is the posterior probability of the B-SVAR model parameters. Since Markov chain Monte Carlo (MCMC) methods are used to sample and estimate the B-SVAR model, we can compute a modified harmonic mean of the log marginal data density (MHM $log(MDD)$) in equation (8). This weighted mean is used to account for the correlation in the posterior estimates produced by MCMC sampling (Gelfand and Dey 1994, Geweke 1999).[30] Once the modified harmonic mean of the $log(MDD)$ is found one

[30]The modified harmonic mean is a weighted mean for the maximum of the log MDDs from the sampling algorithm

can summarize its mean squared error and 68% highest posterior density region (approximately 1 standard deviation around the mean) and the mean squared error of the $log(MDD)$ using the MCMC sample for the parameters.[31]

Macroeconometricians often rely on evaluations of the dynamics—especially, of the impulse responses—in choosing among models because of their concerns about the problems of observational equivalence and overfitting. They work with the models that produce the most plausible impulse responses to shocks in equations. They emphasize accuracy of dynamic responses via the location, shape and skewness of the error bands for the responses. In our illustration, we too use impulse responses to help choose a model. We employ Bayesian error bands for this purpose.[32] In sum, model fit and assessments of uncertainty are in a sense subjective. The Bayesian approach produces a strong preference for probability measures of the posterior distribution of the parameters and of impulse responses.

3 A B-SVAR Model of the American Political Economy

Modeling the connections between the American economy and political opinion has been a major goal in American politics. One major contribution to this endeavor is the aggregate analysis of the economy and polity by Erikson, MacKuen and Stimson (2002, Chapter 10). Hereafter we abbreviate these authors as EMS. EMS construct a recursive model where economic factors are used to predict political outcome (e.g., presidential approval). 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 enhance our ability to analyze American macro-political dynamics.[33]

with weights declining harmonically from the peak.

[31] We note that these quantities are computationally expensive and are not widely seen in the literature.

[32] Brandt and Freeman (2006) explain how these and other kinds of error bands for impulse responses are constructed including the Bayesian shape error bands developed by Sims and Zha (1998, 1999). In that article we illustrate the different types of error bands in an example from international relations.

[33] 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 more computational than empirical. To avoid the "nightmare of endogeneity" EMS use lags and impose a strong

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

We begin by constructing a nine equation system that incorporates the major features of the existing knowledge about the 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 of Sims and Zha (1998) and Leeper, Sims and Zha (1996). Hereafter we abbreviate Leeper, Sims and Zha, and Sims and Zha as LSZ and SZ, 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 sector" of the macro-political economy. The political sector of the model consists of three equations: macropartisanship (MP), presidential approval (A), and consumer sentiment (CS).[34] Since presidential approval and consumer sentiment are in large part the result of economic evaluations, the dynamics of the macroeconomy figure prominently in EMS' 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.[35] To model the objective economic factors and policy that citizens evaluate we utilize the empirical 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 U.S. (*inter alia* Sims 1986*a*, Leeper, Sims and Zha 1996, Sims and

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. There is a report of an exogeneity test (123, fn. 8). But most of the identifying restrictions for EMS's model are posited, not established through any analyses of the data. We build a large scale model that allows for complex, theoretically justified endogeneity, dynamics and contemporaneous causal structure instead of assuming that the American political economy is recursive. The Bayesian approach allows the use of a unified statistical framework for assessing model uncertainty and for making inferences.

[34]Presidential approval and macropartisanship marginals are from Gallup surveys obtained from the Roper Center and iPoll; missing values for some months are linearly interpolated. Consumer sentiment 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/.

[35]See the concluding chapter of *The Macropolity* especially pages 444–448. EMS quote Alesina and Rosenthal's (1995, 224) argument 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.

Zha 1998, Robertson and Tallman 2001). These six economic variables are grouped into four economic sectors or equations. 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 demand* 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).[36] The interest rate, approval, and macropartisanship variables are all expressed in percentage points while the other variables are in natural logarithms.[37] All of the variables are monthly from January 1978 until June 2004 (the monthly measure of the Michigan Index of Consumer Sentiment).[38]

These nine endogenous variables—the six economic variables plus the Michigan Index of Consumer Sentiment, presidential approval and macropartisanship—are modeled as 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 a presidential party variable that is coded -1 = Republican, 1 = Democrat, which allows us to account for the different effects of the variables across administrations. This achieves the same effect in our model as the "mean centering" of the consumer sentiment and presidential approval variables in Green, Palmquist and Schickler (1998). The final exogenous variable is an election counter which runs from 1 to 48 over a four year presidential term to capture election cycle effects, as suggested by Williams (1990).[39]

[36] Data on most economic variables and consumer sentiment 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 at http://www.crbtrader.com/crbindex/. The monthly real GDP series were 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).

[37] The reason for these transformations is that our subsequent dynamic responses for the logged variables will all be interpretable in percentage terms for each variable.

[38] 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 the their analyses since we include data from 1978–2004. Second, we are working with monthly data, which means our analysis will contain more sampling variability than the aggregated quarterly data used by EMS. We use monthly data because their arguments imply different reaction times for approval and macropartisanship to changes in the economy and consumer sentiment.

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

There are two steps to specifying 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 2. (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 non-empty cells (marked with X's) are contemporaneous structural relationships to be estimated while the empty cells are constrained to be zero.

We must provide a rationale for the contemporaneous restrictions and relationships. Beginning with the economic sectors, the restrictions for the Information, Monetary Policy, Money Demand and Production sectors come from leading studies in macroeconomics (see e.g., Sims 1986*b*, Williams 1990, Robertson and Tallman 2001, Waggoner and Zha 2003*a*).[40] 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 (those in the three right-most columns and first six rows of Table 2). To allow for political accountability, contemporaneous effects are specified for political variables in two of the economic equations. First, the macropolity variables—approval, consumer sentiment, and macropartisanship can have a contemporaneous effect on commodity prices.[41] This is consistent with recent results in international political economy such as Bernhard and Leblang (2006). Second, presidential approval is expected to 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

[40]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, while 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_+.

[41]We thank an anonymous reviewer for suggesting the endogenous relationship between macropartisanship and the information sector.

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 2. 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 2) allows all of the production sector variables to contemporaneously affect the macropolity variables: innovations in GDP, unemployment, and prices have an immediate effect on consumer sentiment, approval, and macropartisanship. 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, Clarke, Ho and Stewart 2000, Green, Palmquist and Schickler 1998). We also specify a recursive contemporaneous relationship among the consumer sentiment, approval, and macropartisanship variables. This is suggested by the discussion (purging) 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 2 has 38 free parameters. Hence, it A_0 is over-identified.[42]

[Table 2 about here.]

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 which 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

[42]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.

macropartisanship 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 approval and consumer sentiment do not have unit roots, which is still possible with these beliefs. We denote this prior by the name "EMS-SZ Tight".

Because these hyperparameters are not directly elicited from EMS, it is wise to consider alternative representations of their beliefs. A sensitivity analysis is recommended in an investigation like this, as noted above (Gill 2004, Jackman 2004). We therefore propose three additional prior specifications. The second, allows for more uncertainty than the EMS and SZ prior (larger standard deviations for the parameters and less weight on the sum of autoregressive coefficients and impact of the initial conditions). This belief could be based on the evidence that political variables like macropartisanship are not long-memoried (for instance Box-Steffensmeier and Smith 1996). We denote this second prior, "EMS-SZ Loose". On the basis of a grid search from among 512 possibilities, we also found the hyperparameters that produced the largest $log(MDD)$. This prior is called simply "Best MDD".[43] The fourth 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 a B-SVAR model with two informed and two uninformed priors. The priors are summarized in the Table 3.

[Table 3 about here.]

[43]We employ a grid search to look at different priors. We examined prior specifications based on combinations of the following hyperparameter values: $\lambda_1 = \{0.1, 0.15\}$, $\lambda_3 = \{1, 2\}$, $\lambda_4 = \{0.1, 0.2\}$, $\mu_5 = \{0, 1, 2, 3, 4, 5, 6, 7\}$ and $\mu_6 = \{0, 1, 2, 3, 4, 5, 6, 7\}$ (a total of $2 \times 2 \times 2 \times 8 \times 8 = 512$ priors). The posterior is most sensitive to the choice of the lag decay variance (λ_3) and the beliefs about unit roots and cointegration. The λ_0 hyperparameter is set equal to 0.6 to reflect the increased sampling variability of our monthly time series relative to quarterly data.

3.2 Results

We first present results about the overall fit of the model with each of the four priors. After selecting a prior based on the fit measures, we then turn to the dynamic inferences. Note that 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.[44] As suggested earlier, the modified harmonic means of the log marginal data density (MHM $log(MDD)$) are used to compare the impact of the prior on the posterior.[45] We also compute 1) the 68% highest posterior density region (approximately 1 standard deviation around the MHM $log(MDD)$) and 2) the mean squared error of the MHM $log(MDD)$ from the posterior sample using the modified harmonic mean as the mean estimate. Finally, we compute a loss function statistic of primary interest: the mean squared error (MSE) of modified harmonic mean of the $log(MDD)$.

Table 3 shows that in terms of the MSE loss criterion the informed priors are superior to the uninformed priors. The modified harmonic mean values for the posterior log marginal data density is highest for the diffuse prior. But the MSE loss for this quantity is more than 2.5 times larger than any of the other priors. This is because the diffuse prior model overfits the data. While the uninformed priors have posterior MHM $log(MDD)$ values that are larger than EMS-SZ priors, the MSE around these posterior peaks are larger than those for the informed priors. The 68% confidence regions for the uninformative priors are between 5 and 15% larger than those of the informed priors. Interestingly, the EMS-SZ Loose prior is better than the EMS-SZ Tight prior on the MSE loss criterion. The former generates a posterior with smaller MSE and larger MHM $log(MDD)$ than the EMS-SZ Tight prior.

As stressed earlier, comparison of posterior summaries does not show how pivotal quantities of

[44] 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.

[45] All posterior fit results are for a posterior sample of 40000 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. Thus, we are confident that the sampler has converged.

interest such as impulse responses respond to prior specifications. The choice of a B-SVAR model and prior should depend on its dynamics. For each of the four priors in Table 3 we computed the impulse responses for the full nine equation system. Based on the $log(MDD)$ and impulse responses, we present the results for the EMS-SZ Loose prior. The model with the EMS-SZ Loose prior produces the most theoretically meaningful dynamics. The impulse responses for the diffuse prior model have error bands than are vary widely and make interpretation of the magnitudes and direction of the dynamics impossible. The Best MDD prior generates impulse responses that do not conform to expectations. The Best MDD prior has impulse responses with a) incorrect monetary policy responses, b) long term reactions in some variables (such as approval changes permanently lowering unemployment) that are a priori impossible, or c) approval effects in monetary policy (M2) rather than money demand (interest rates or R) as previously documented in the literature (Williams 1990). In contrast, the results with the two informed priors differ in a reasonable way. The responses to shocks in with the EMS-SZ Tight prior are more permanent and dissipate more slowly than those in the EMS-SZ 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 EMS-SZ Tight prior).[46]

We focus on two sets of impulse responses for the model with the EMS-SZ Loose prior. The first are the responses of the economy to changes in politics. Figure 1 presents the subset of the responses of the economic equations to shocks in the macropolity sector variables.[47] Each row are the responses for the indicated equation for a shock in the column variable. Responses are median estimates with 68% confidence region error bands, computed pointwise over a 48 month time horizon.[48] The interpretation of the impulse responses differs from those typically seen in

[46]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.

[47]These responses were generated using the Gibbs sampler for B-SVAR model in Waggoner and Zha (2003*a*). This Gibbs sampler draws samples from the posterior distribution of the restricted (over-identified) 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 20000 draws after a burnin of 2000 draws. Similar results were obtained for a posterior sample twice as large using two independent MCMC chains.

[48]Sims and Zha (1999) argue that 68% error bands (which are approximately one standard deviation bands) provide a better summary of the central tendency or likelihood of the impulse responses. Further discussion and examples of

the literature. In standard reduced form VAR models with a recursive identification of the contemporaneous error covariance, one analyzes the responses to *positive shocks* to each equation in the system. Such a normalization of the shocks is not possible in non-recursive B-SVAR models (Waggoner and Zha 2003*b*). Since the contemporaneous shocks to a set of equations may be (negatively) correlated with each other in the non-recursive system, shocks or innovations of different signs may enter each equation. Thus positive shocks to one equation may imply negative shocks to other equations (e.g., structural shocks to the inflation and unemployment equations should have opposite signs because of their Philips' curve relationship).

[Figure 1 about here.]

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 consumer sentiment lead to lagged increases in commodity prices, reaching a maximum of 0.1% over 30 months. Similarly, increases in approval generate less than 0.05% decreases in commodity prices. With respect to the monetary policy and money demand sectors (M2 and R), changes in consumer sentiment and approval affect interest rates, but not monetary policy. These shocks enter the interest rate equation negatively so declines in consumer sentiment increase interest rates (with the lower edge of the 68% confidence region at zero) while declines in approval lead to lower interest rates over 10-12 months. Thus, consumer sentiment (presidential approval) and interest rates are positively (negatively) related. Note that the consumer sentiment shock generates an interest rate response that is nearly twice as large and in the opposite direction of the approval shock over 48 months.

The interest rate and money responses 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.

why this is a preferable confidence region can be found in Brandt and Freeman (2006).

For the production sectors—real GDP (Y), inflation (CPI), and unemployment (U)—the political shocks generate responses as well. Real GDP does not respond to political shocks, as the confidence regions are large and cover zero. Positive shocks in consumer sentiment and approval lead to higher inflation as the CPI responses to these shocks increase, albeit with a lag. Note though that these responses are small—always less than 0.008%. The median total response of CPI to the consumer sentiment and approval innovations over 48 months is less than 0.2%.[49] The shocks to the unemployment equation enter negatively, so decreases in consumer sentiment lower unemployment by at most 0.05% with a lag over 48 months. Over 48 months the median total response of unemployment to innovations in consumer sentiment is a -1.82 point decline in unemployment (68% credible interval [-2.03, -1.62]). Similarly, declines in approval increase unemployment, peaking at about a 0.02% change 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 other side of the B-SVAR system are the impacts of the economy on the macropolity. Figure 2 present the full set of responses for the macropolity equations. Here we can judge the relative impacts of different economic and political shocks on consumer sentiment, approval, and macropartisanship. In the consumer sentiment and macropartisanship equations the response to their own shocks is positive so shocks enter these equations as positive one standard deviation changes. In contrast, the approval equation the response to its own shock is negative so shocks enter this equation as negative one standard deviation changes. Thus each plot in the figure is the impact of a signed one standard deviation change in the column variable to the row equation. Consumer sentiment responds most strongly to commodity price and approval shocks. One standard deviation increases in commodity prices (in percentage terms, about 0.25%) lowers consumer sentiment by a maximum of 0.17 points over 48 months. In cumulative terms, this same increase in commodity prices lowers the median consumer sentiment by a full 4.5 points (68% credible interval [-6.98, -2.21]) over 48 months. In contrast, the one standard deviation increase in presidential approval

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

raises consumer sentiment a median total impact 1.96 points over 48 months (68% credible region [1.28, 2.71]).

[Figure 2 about here.]

Commodity prices, consumer sentiment and approval's own innovations have the largest impact on approval responses. A one standard deviation negative shock to commodity prices lowers approval by a maximum of 0.15 points over 48 months. This cumulates to a median total change of nearly -3.5 points for an initial quarter percent drop in commodity prices (68% credible interval [-6.35, -0.79]). Thus, information markets have a wide degree of influence on both consumer sentiment and approval. The effect of consumer sentiment shocks on approval reflects this as well. The magnitude of the median total effect of the impact of consumer sentiment on approval is large. Over 48 months, a one standard deviation drop in consumer sentiment lowers approval by a total median impact of -1.6 points; at 48 months the probability that the cumulative response of approval to the consumer sentiment shock is negative is 0.73. Thus, innovations in information markets impact consumer sentiment and approval and then the impacts on consumer sentiment feed-forward into subsequent approval changes. Note however that the real economy does not have 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. Consumer sentiment responds mainly to its own shocks and not those of the other political variables (not even with a lag). The consumer sentiment response to approval shocks is small over 48 months. Neither consumer sentiment nor approval respond to changes in macropartisanship.

One of the main questions for both our analysis and for EMS is the exploration of what moves aggregate partisanship? The final row of plots in Figure 2 shows the responses for the macropartisanship equation. Positive shocks in the production sector and in presidential approval have no sizeable impact on aggregate partisanship. The response of macropartisanship to positive one standard deviation shocks in commodity prices and consumer sentiment are suggestive, but weak. Over

48 months the positive commodity price and consumer sentiment shocks lower macropartisanship by only about 0.05%. The impact of these shocks on macropartisanship does not cumulate to even a one point change over 48 months. In the end, the macropartisanship equation is mainly driven by shocks to macropartisanship 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 macropartisanship usually reveals how researchers conceive of some of these relationships. Admittedly, scholars sometimes 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 of 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.[50]

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

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

and Zha 1997). Some researchers contend that formal models produce more useful structural insights than VAR models (structural, reduced form 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.[51]

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 study of the macropolity.[52]

[51]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.

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

A Bayesian Structural VAR specification and estimation

A.1 Posterior for the model

The structural model can be transformed into a multivariate regression by defining A_0 as the contemporaneous correlations of the series and A_+ as a matrix of the coefficients on the lagged variables by

$$YA_0 + XA_+ = E, \tag{9}$$

where Y is $T \times m$, A_0 is $m \times m$, X is $T \times (mp+1)$, A_+ is $(mp+1) \times m$ and E is $T \times m$. Here we have placed the constant as the last element in the respective matrices. Note that the columns of the coefficient matrices correspond to the equations.

To derive the Bayesian estimator for this structural VAR model, we need the conditional likelihood function for its normally distributed residuals:

$$\begin{aligned} L(Y|A) &\propto |A_0|^T \exp\left[-0.5tr(ZA_+)'(ZA_+)\right] && (10)\\ &\propto |A_0|^T \exp\left[-0.5a_+'(I \otimes Z'Z)a_+\right] && (11) \end{aligned}$$

where $tr()$ is the trace operator. This is a standard multivariate normal likelihood equation.

The posterior for the model coefficients is formed by combining the likelihood function with the prior:

$$\begin{aligned} q(A) &\propto L(Y|A)\pi(a_0)\phi(\widetilde{a_+}, \Psi) && (12)\\ &\propto \pi(a_0)|A_0|^T|\Psi|^{-0.5} \times \exp[-0.5(a_0'(I \otimes Y'Y)a_0 \\ &\quad -2a_+'(I \otimes X'Y)a_0 + a_+'(I \otimes X'X)a_+ + \widetilde{a_+}'\Psi\widetilde{a_+})]. && (13) \end{aligned}$$

A.2 Scaling the prior covariance of the parameters

To see how the hyperparameters in Table 1 work to set the prior scale of A_+, remember that $V(A_+|A_0) = \Psi$ is the prior covariance matrix for $\widetilde{a_+}$. Each element of Ψ then corresponds to the variance of the VAR parameters. The variance of each of these coefficients has the form

$$\psi_{\ell,j,i} = \left(\frac{\lambda_0 \lambda_1}{\sigma_j \ell^{\lambda_3}}\right)^2, \tag{14}$$

for the element of Ψ corresponding to the ℓ^{th} lag of variable j in equation i. The overall coefficient covariances are scaled by the value of the error variances from m univariate AR(p) OLS regressions of each variable on its own lag values, σ_j^2 for $j = 1, 2, \ldots, m$.[53] The parameter λ_0 sets an overall tightness across elements of the prior on $\Sigma = A_0^{-1'} A_0^{-1}$, which relates the reduced form error covariance Σ to the contemporaneous structural relationships in A_0. As λ_0 approaches 1, the conditional prior variance of the parameters is the same as in the sample residual covariance matrix, while smaller values imply a tighter overall prior. The hyperparameter λ_1 controls the tightness of the beliefs about the random walk prior or the standard deviation of the coefficients on first lags (since $\ell^{\lambda_3} = 1$ in this case). The ℓ^{λ_3} term allows the variance of the coefficients on higher order lags to shrink as the lag length increases. The constant in the model has a separate prior variance of $(\lambda_0 \lambda_4)^2$. Any exogenous variables can be given a separate prior variance proportionate to a parameter λ_5 so that the prior variance on the coefficients of any exogenous variable is $(\lambda_0 \lambda_5)^2$.

[53] This is the only use of the sample data in the specification of the prior. The only reason the data are used in this way is so the scale of the prior covariance is proportionate to the sample data.

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

Table 1: Hyperparameters of Sims-Zha Reference Prior

Sector	Variables	Pcom	M2	R	Y	CPI	U	CS	A	MP
Information	Pcom	X	X	X	X	X	X	X	X	X
Monetary Policy	M2		X	X					X	
Money Demand	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	A				X	X	X	X	X	
Macropolity	MP				X	X	X	X	X	X

Table 2: General Framework for Contemporaneous Relationships in the U.S. Political Economy. The X's (empty cells) represent contemporaneous relationships to be estimated (restricted to zero) in the Bayesian SVAR model.

Hyperparameter	EMS-SZ Tight	EMS-SZ Loose	Best MDD	Diffuse
Error covariance matrix scale (λ_0)	0.6	0.6	0.6	1
Standard deviation of A_1 (persistence) (λ_1)	0.1	0.15	0.2	10
Decay of lag variances (λ_3)	1	1	1	0
Standard deviation of intercept (λ_4)	0.1	0.15	0.2	10
Standard deviation of exogenous variables (λ_5)	0.07	0.07	0.07	10
Sum of autoregressive coefficients component(μ_5)	5	2	0	0
Correlation of coefficients/Initial condition component (μ_6)	5	2	1	0
MHM of $log(MDD)$	11368	12204	12866	19216
68% HPD for MHM of $log(MDD)$	[11512,12307]	[12362,13155]	[13036,13863]	[19489,20405]
MSE of MHM $log(MDD)$	4154	3680	4428	11130

Table 3: Four B-SVAR priors and their posterior fit measures

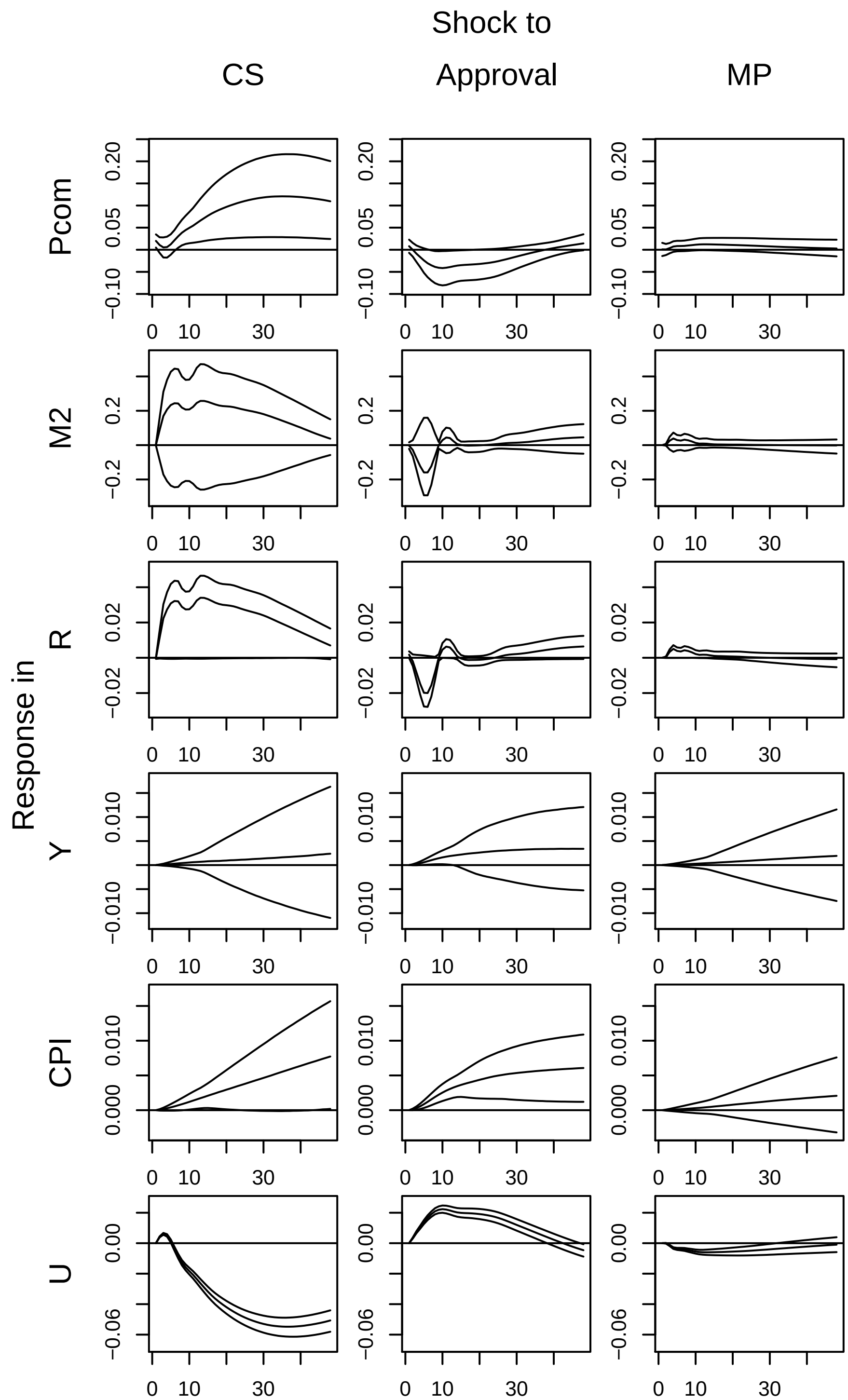

Figure 1: Impulse Responses of the Economic Sectors to Political Shocks Over 48 Months. Responses are median responses computed from the B-SVAR posterior. Error bands are 68% or approximately one standard deviation around the median response. Shocks to the Pcom, M2, Y, and CPI (row) equations are positive one standard deviation innovations in the column variables. Shocks to the R and U (row) equations are negative one standard deviation innovations in the column variables. See the text for discussion and interpretation.

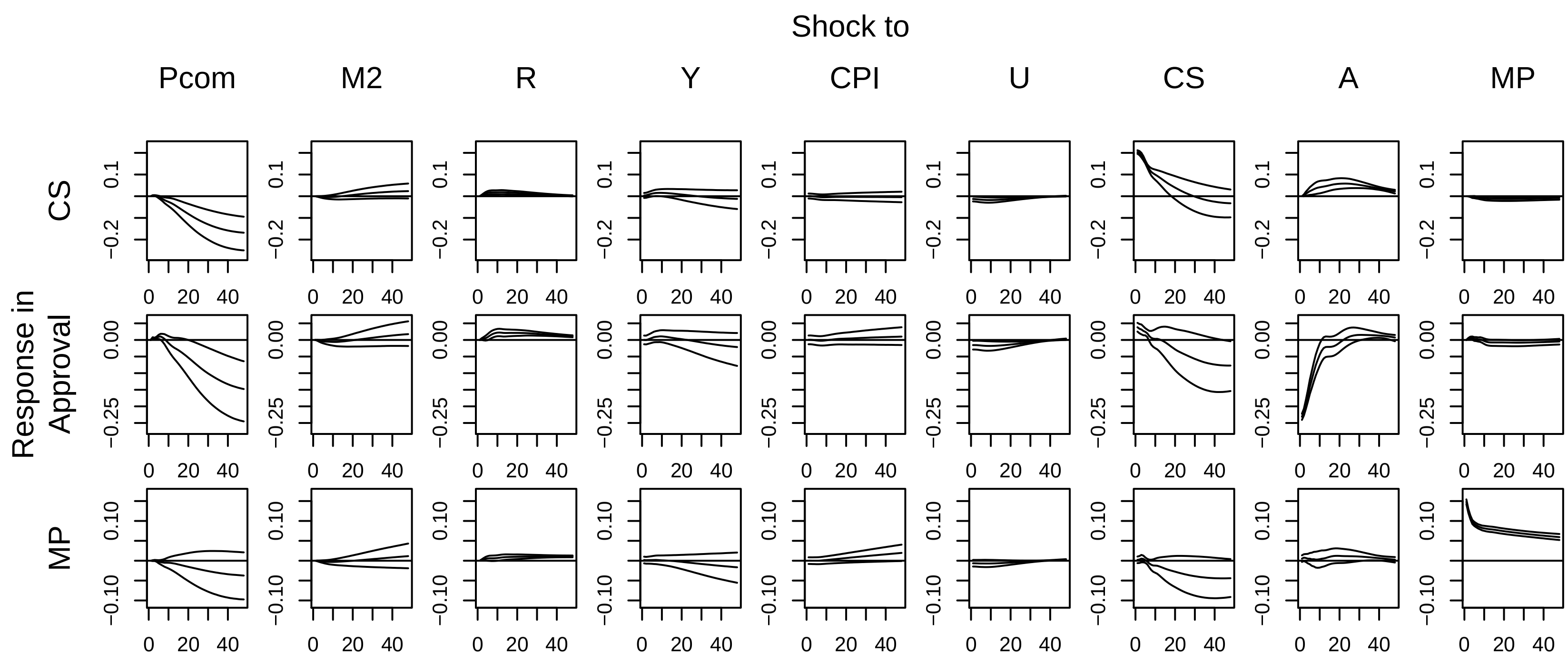

Figure 2: Impulse Responses of the Macropolity Sectors to Economic Shocks Over 48 Months. Responses are median responses computed from the B-SVAR posterior. Error bands are 68% or approximately one standard deviation around the median response. Shocks to the consumer sentiment and macropartisanship (row) equations are positive one standard deviation innovations in the column variables. Shocks to the approval (row) equation are negative one standard deviation innovations in the column variables. See the text for discussion and interpretation.