

# BAYESVAR

## A MATLAB PACKAGE FOR BAYESIAN VARS

MATTIAS VILLANI

ABSTRACT. This is an instruction manual for a MATLAB (Windows) program to analyze reduced form and structural vector autoregressions (VAR), possibly with informative priors on the steady state. All user inputs and data are supplied to MATLAB via a user-friendly Microsoft Excel interface. The package includes methods for i) simulating from the posterior distribution of the VAR model parameters, ii) dynamic unconditional and conditional forecasting, iii) forecast evaluations, iv) impulse response analysis, v) variance and historical decompositions, vi) model diagnostic tools, such as plot of actual and fitted values, residual histograms and correlograms.

### CONTENTS

1. Getting started	4
2. Models in BayesVAR	4
3. Priors in BayesVAR	5
4. Simulating from the posterior distribution	6
5. Simulating from the forecast distribution	7
6. Structural analysis	8
7. Forecast evaluation	8
8. Managing the BayesVAR Excel workbook	9
8.1. Options	9
8.2. Endo and Exo	10
8.3. Endoproperties and Exoproperties	10
8.4. Identification	11
8.5. CondForecast	12
Appendix A. Details of the Options sheet	15
References	31



## DISCLAIMER OF WARRANTY AND LIMITATION OF LIABILITY

This MATLAB package BayesVAR comes with no warranty. The author of BayesVAR, Mattias Villani, cannot be held liable for any damages arising out of the use of this program.

## 1. GETTING STARTED

BayesVAR is a set of MATLAB 7 routines for analyzing Bayesian vector autoregressions (VAR). All user inputs (data, model, estimation, simulation and forecasting settings etc.) are supplied via an Excel workbook, which is then read and analyzed by MATLAB.

To start a new project it is suggested that you go through the following steps:

- Use Windows Explorer to create a new subfolder under `c:\BayesVAR\Projects` (assuming that BayesVAR is located on the c-drive). Let us, as an example, name this folder `MyProject`.
- Create a BayesVAR Excel workbook with all data and model inputs (tip: modify the existing workbook `FirstExample.xls` in `c:\BayesVAR\Projects\FirstExample`). Save the created BayesVAR Excel workbook in the folder `MyProject` as `MyWorkbook.xls`.
- Start MATLAB and set the current directory to `c:\BayesVAR\Projects\MyProject`.
- Place the BayesVAR folder and all its subfolders on the MATLAB path, so that MATLAB can access the BayesVAR code. This can be done by choosing the *Set Path ...* option on the *File* menu and then choosing *Add with Subfolders ...*. Save the changes to the MATLAB path. This needs to be done only once.
- Type `BayesVAR` at the MATLAB prompt and press the enter key.
- Select the BayesVAR Excel workbook `MyWorkbook.xls` in the file input dialog window.
- BayesVAR then reads all data and settings, performs the computations, and displays the results in text files and graphs.

## 2. MODELS IN BAYESVAR

The base model used in the BayesVAR package is the (reduced form) Vector Autoregressive (VAR) process with  $K$  lags:

$$(2.1) \quad x_t = \sum_{k=1}^K \Pi_k x_{t-k} + \Phi d_t + u_t, \quad (t = 1, \dots, T),$$

where  $x_t$  is  $p$ -dimensional column vector with observations on  $p$  time series at time  $t$ .  $d_t$  contains the exogenous variables, deterministic constants and trends. The  $u_t$  are the reduced form shocks which are assumed to be *iid* multivariate normal with zero mean

and covariance matrix  $\Sigma$ . The BayesVAR package can also work with structural VARs:

$$(2.2) \quad \Upsilon x_t = \sum_{k=1}^K \Pi_k x_{t-k} + \Phi d_t + \varepsilon_t, \quad (t = 1, \dots, T),$$

where  $\Upsilon$  is a  $p \times p$  matrix with contemporaneous coefficients, and the structural disturbances  $\varepsilon_t$  are *iid* normal with zero mean and identity covariance matrix. BayesVAR uses zero restrictions on the coefficient in  $\Upsilon$  (including Cholesky/Recursive identification) to identify the model.

BayesVAR can also handle the steady-state formulation of the VAR (Villani, 2007)

$$(2.3) \quad x_t - \Psi d_t = \sum_{k=1}^K \Pi_k (x_{t-k} - \Psi d_{t-k}) + u_t, \quad (t = 1, \dots, T),$$

where  $\Psi d_t$  is an explicit formulation of the process' steady state. The advantage of this parametrization is that priors can be formulated directly on the steady state. The Steady-State VAR can also be analyzed on structural form.

### 3. PRIORS IN BAYESVAR

The prior on the reduced form errors covariance matrix  $\Sigma$  is the usual non-informative prior for a covariance matrix:

$$p(\Sigma) \propto |\Sigma|^{-(p+1)/2}.$$

All coefficients in  $\Pi_1, \dots, \Pi_K$  are assumed to be independent and normally distributed a priori (see below on imposing stationary, however). The mean of the coefficients are assumed to be zero with the exception of the diagonal elements in  $\Pi_1$  that can be set to any number (see column **Mean on First Lag** in the Excel sheet **Endoproperties**). If the standard form of the VAR in (2.1) is used, then the elements in  $\Phi$  are normally distributed, mean zero and standard deviation  $\lambda_5 > 0$ . If the steady state VAR in (2.3) is used, then the prior on the elements of  $\Psi$  are normal, with means and standard deviations specified in the Excel sheet **Endoproperties**. If the structural form of the model in (2.2) is used, then the unrestricted elements of  $\Upsilon$  are assigned uniform priors.

Let  $\pi_{ij}^{(k)}$  be the coefficient on the  $j$ th variable's  $k$ th lag in the equation for the  $i$ th endogenous variable (i.e.  $\pi_{ij}^{(k)}$  relates  $x_{j,t-k}$  to  $x_{i,t}$ ). Following Litterman (1986), we model the prior standard deviation of  $\pi_{ij}^{(k)}$  as

$$S(\pi_{ij}^{(k)}) = \begin{cases} \frac{\lambda_1 s_i}{k^{\lambda_3} s_j} & \text{if } i = j \text{ (own lag)} \\ \frac{\lambda_1 \lambda_2 s_i}{k^{\lambda_3} s_j} & \text{if } i \neq j \text{ (cross-equation lag)} \end{cases},$$

where  $\lambda_1 > 0$  is the overall shrinkage,  $0 < \lambda_2 \leq 1$  is the cross-equation shrinkage,  $\lambda_3 > 0$  is the lag decay parameter.  $s_i$  is the standard deviation of the residuals from fitting an univariate  $AR(K)$  process with exogenous variables  $d_t$  to the  $i$ th endogenous variable. The  $s_i$  are included to control for the differing scales of the variables. There is an additional shrinkage parameter ( $0 < \lambda_4 \leq 1$ ) that is very useful in small open economy models. If  $\pi_{ij}^{(k)}$  is a coefficient that models the effect of a variable in a small economy on a variable in a large economy, then prior standard deviation is modelled as

$$S(\pi_{ij}^{(k)}) = \frac{\lambda_1 \lambda_2 \lambda_4 s_i}{k^{\lambda_3} s_j},$$

where  $0 < \lambda_4 \leq 1$ . Block exogeneity can therefore be implemented with an arbitrarily large probability by setting  $\lambda_4$  to an increasingly small number.

The Litterman prior makes the prior tighter around zero for longer lags. When data contains seasonality it may be preferable to handle the seasonal lags (lag 4,8,12, etc. for quarterly data) differently from the non-seasonal lags. The prior hyperparameter  $0 < \lambda_6 \leq 1$  can be used to implement this. As an example, if  $\lambda_6 = 1$ , then lag 4 has the same standard deviation as lag 1, lag 8 has the same standard deviation as lag 2 etc.

See the the Excel sheet *Options/Load prior from file* on how to specify a general multivariate prior for the VAR coefficients.

#### 4. SIMULATING FROM THE POSTERIOR DISTRIBUTION

BayesVAR simulates from the joint posterior distribution of all model parameters using Gibbs sampling. Gibbs sampling simulates iteratively from the full conditional posterior distributions, the posterior distribution of a parameter subset (block) conditional on all other parameters of the model. A parameter block is drawn from the posterior distribution by conditioning on the most recent draw of the other model parameters.

In the Standard BVAR in (2.1) we simulate from the following two blocks of parameters (Karlsson and Kadiyala, 1997)

$$\begin{aligned} \text{vec } \Pi | \Sigma &\sim \text{Multivariate Normal} \\ \Sigma | \Pi &\sim \text{Inverted Wishart} \end{aligned}$$

where  $\Pi = (\Pi_1, \dots, \Pi_K, \Phi)$ . Note here that  $\Phi$  is sampled in the same block as the dynamic coefficients  $\Pi_1, \dots, \Pi_K$ . In the Steady-State VAR (2.3) we use three updating

blocks (Villani, 2007):

$$\begin{aligned} \text{vec } \Pi | \Sigma, \Psi &\sim \text{Multivariate Normal} \\ \Sigma | \Pi, \Psi &\sim \text{Inverted Wishart} \\ \text{vec } \Psi | \Pi, \Sigma &\sim \text{Multivariate Normal.} \end{aligned}$$

If a non-recursive Structural VAR is used (2.2), then the contemporaneous parameters,  $\Upsilon$ , are simulated using the updating step in Waggoner and Zha (2003b). In this case  $\Sigma$  is of course not simulated.

There is an option in BayesVAR to discard  $\Pi$ -draws that implies a non-stationary VAR process (*Restrict VAR to be stationary*).

BayesVAR obtains the posterior distribution of any (nonlinear) function of the parameters, e.g. impulse responses and variance decompositions, by evaluating that function on every parameter draw.

## 5. SIMULATING FROM THE FORECAST DISTRIBUTION

Let  $\theta$  denote the set of all model parameters, e.g.  $\theta = (\Pi, \Sigma, \Psi)$  in the Steady-State BVAR. The  $h$ -step-ahead dynamic forecast density at time  $T$  is then

$$p(x_{T+1}, \dots, x_{T+h} | x^{(T)}) = \int p(x_{T+1}, \dots, x_{T+h} | \theta, x^{(T)}) p(\theta | x^{(T)}) d\theta,$$

where  $x^{(T)} = (x_1, \dots, x_T)$  contains all historical data up to time  $T$ . To simplify notation, we have not explicitly written out the conditioning on the deterministic variables,  $d_1, \dots, d_T$ . We obtain draws from the forecast density as follows:

- (1) Simulate a  $\theta$  from the posterior distribution by Gibbs sampling
- (2) Simulate the VAR process  $h$ -steps forward, conditional on the generated  $\theta$  in Step 1.
- (3) Repeat Steps 1 and 2 until convergence to the predictive density has been obtained.

The collection of all these dynamic simulations (one for each  $\theta$ -draw) is then used to approximate the point forecast (median) and the forecasting intervals (quantiles of the forecasting density).

BayesVAR can also produce conditional forecasts, i.e. forecasts of  $x_t$  conditional on pre-specified paths for a subset of the endogenous variables in  $x_t$ . Conditioning on paths of the endogenous variables puts restrictions on the structural errors during the

forecasting period,  $\varepsilon_{T+1}, \dots, \varepsilon_{T+h}$ . Section 8.5 gives the details of BayesVARs flexible conditional forecasting routine.

## 6. STRUCTURAL ANALYSIS

BayesVAR computes and graphs the posterior distribution of variance decompositions and impulse responses. The VAR models are identified with zero-restrictions on the contemporaneous coefficients in  $\Upsilon$  in (2.2). The recursive/Choleski identification is also an option. See Section 8.4 for details on how to implement an identification scheme in BayesVAR.

BayesVAR also computes various historical decompositions. A historical decomposition answers the question: what would the data have looked like if a subset of the shocks had been zero throughout the estimation period? This can be a very useful tool for understanding the driving forces (shocks) in the economy. BayesVAR also has the options to turn off a subset of shocks only from a certain date and onward.

## 7. FORECAST EVALUATION

BayesVAR assesses out-of-sample forecasting performance using a sequential forecasting procedure with the VAR parameters estimated using data up to a specified time period  $T$  (**First forecast date** in the Option sheet) where the dynamic forecast distribution of  $x_{T+1}, \dots, x_{T+h}$  is computed. The estimation sample is then extended to include the observed data at time  $T+1$  and the dynamic forecast distribution of  $x_{T+2}, \dots, x_{T+h+1}$  is computed. This is prolonged until the specified **Last forecast date** in the Options sheet.

BayesVAR evaluates the accuracy of point forecasts, interval forecasts and density forecasts. Many different measures of accuracy (univariate and multivariate) can be used, see Table 1 for a brief description and Adolfson, Lindé and Villani (2007) for details. BayesVAR also plots the actual data and all the sequential forecast paths (Cascade plot). The posterior estimates of the VARs steady state are also plotted over the forecast evaluation period. The current version of BayesVAR does not support real-time forecast evaluations with data that are subject to revisions.

BayesVAR includes a few commonly used benchmark forecasts. The **no-change forecast** produced at time  $t$  is defined as

$$\hat{x}_{t+h|t} = x_t, \quad (h = 1, \dots, H).$$

	Univariate	Multivariate
Point forecasts	Root Mean Squared Errors (RMSE) Mean Absolute Errors (MAE) Mean Absolute Percentage Errors (MAE) Mean Percentage Error (MPE)	LogDetMSSE TraceMSSE
Interval forecasts	Empirical coverage Bayes test for hit sequences	-
Density forecasts	Log Predictive Density Score (LPDS)	LPDS

TABLE 1. Measures of Out-of-Sample Forecast Accuracy in BayesVAR.

BayesVAR produces two different no-change forecasts for variables in growth rates, one defined on the period-to-period growth rates (e.g.  $\ln(x_{t+1}/x_t)$ ) (**NoChange**) and the other on yearly growth rates (e.g.  $\ln(x_t/x_{t-4})$  for quarterly data) (**NoChange Yearly**). The **recent mean forecast** is the mean of the  $r$  most recent realized values

$$\hat{x}_{t+h|t}^{(r)} = r^{-1} \sum_{i=1}^r x_{t-i+1}, \quad (h = 1, \dots, H).$$

## 8. MANAGING THE BAYESVAR EXCEL WORKBOOK

BayesVAR constructs a data base with all variables in the **Endo** and **Exo** sheets of the BayesVAR workbook. The user can then choose to model a subset of the variables (as set in the **Options** sheet, see Appendix A). All references to variables in the program is with respect to the original data base, *not* the subset of variables in the current model. As an example, assume that the data base contains six variables  $(x_1, \dots, x_6)$ , but the user chooses to include only variables 2, 3 and 5 in her model. If the user then wants to plot the forecasts of only the two last variables in the modelled VAR system ( $x_3$  and  $x_5$ ), the input to BayesVAR (*Plot predictions for variable* in the **Options** sheet) should be [3 5], not [2 3]. The following subsections describe each of the sheets in the BayesVAR Excel workbook in detail.

**Note:** The names of the Excel *sheets* in the BayesVAR Excel workbook should *not* be changed.

**8.1. Options.** The Options sheet (see the screen shots in Figure 1 and 2) contains more than 60 settings grouped into the categories: DATA, MODEL AND PRIOR, POSTERIOR SAMPLING, FORECASTING, FORECASTING EVALUATION, MODEL FIT, STRUCTURAL VAR and MISC. A detailed description of each option is given in Appendix A.

**8.2. Endo and Exo.** The first column of the **Endo** sheet contains the dates for the observations. The following columns contains data on the endogenous variables. The first row holds the labels for the variables. An example of the **Endo** sheet is given in Figure 3. The **Exo** sheet contains the dates and observations on the exogenous variables (the  $d_t$  in (2.1), (2.2) or (2.3)). This sheet is organized in the same way as the **Endo** sheet. Note: the VAR constant (a column of ones in  $d_t$ ) should *not* be supplied by the user, the program adds it automatically to the set of exogenous variables.

**8.3. Endoproperties and Exoproperties.** The Excel sheets **Endoproperties** (Figure 5) and **Exoproperties** (Figure 6) are used to declare the properties of the endogenous and exogenous variables in the data base. The following properties are set in the **Endoproperties** sheet.

- **LARGE ECONOMY.** Declares if a variable is a large economy variable (this only makes sense in a multiple country model with at least one small and one big economy). Coefficients relating a variable in the small economy to a variable in the large economy may be given additional prior shrinkage towards zero using the prior hyperparameter  $\lambda_4$  (small economies are not likely to affect large economies), see Section 3.
- **DIFFERENCE.** Many VARs include endogenous variables that are modelled in first differences of logs of the original variable (Example 1:  $\pi_t = \ln p_t - \ln p_{t-1}$ , where  $\pi_t$  is the inflation rate at time  $t$  and  $p_t$  is a price index at time  $t$ . Example 2: GDP growth  $\Delta y_t = \ln y_t - \ln y_{t-1}$ , where  $y_t$  is GDP at time  $t$ ). It is usually good practice to report results (e.g. forecasts, fitted values, impulse responses) for such variables in annual growth rates ( $\pi_t^* = \ln p_t - \ln p_{t-4}$ , and  $\Delta y_t^* = \ln y_t - \ln y_{t-4}$ , for quarterly data). Such variables are called **Difference** variables in BayesVAR and special facilities is included in the program to deal with them (i.e. automatically convert the forecasts to annual growth rates). An endogenous variable may be declared as a **Difference** variable in the **Endoproperties** sheet of the Excel workbook. It is of course possible to not declare  $\pi_t$  as a **Difference** variable, the forecasts are then presented in terms of  $\pi_t$ , not  $\pi_t^*$ .
- **MEAN OF FIRST LAG.** This column sets the prior mean of the diagonal elements in  $\Pi_1$ , the endogenous variables coefficients on their own first lag.

- **SEASONAL.** Declares if a variable has seasonality and that its seasonal lags should be shrunk toward zero in a different way from non-seasonal lags. See the discussion of the prior hyperparameter  $\lambda_6$  in Section 3.
- **STEADY-STATE PRIOR.** The columns to the right of the 'Seasonal' column are used to set the prior on  $\Psi$  in the Steady-State VAR (2.3). The first two columns (named `Constant_L` and `Constant_U` in Figure 5) *always* define the lower and upper limits of a prior probability interval for the constant (which is automatically added by BayesVAR, it should **not** be given by the user in the `Exo` sheet). The probability content of this interval is set in the Options sheet (Misc Options/Coverage probability of prior intervals for deterministic components). The subsequent columns specifies the prior on the other exogenous variables in the same way. As an example, if four exogenous variables are used (plus a constant which is added by the program), then there should be 10 columns to the right of the 'Seasonal' column. The last two of these columns would then together specify the prior for the last exogenous variable. Note that these settings are not used when the VAR is specified in Standard form (2.1).

The `Exoproperties` sheet contains only one property: `SMALL ECONOMY`. Declaring an exogenous variable as Small Economy places the additional  $\lambda_4$ -shrinkage on the coefficients on that exogenous variable in the equations for the large economy variables. As an example, if  $\lambda_4$  is set to a very small number (e.g.  $\lambda_4 = 0.01$ ), then the small economy variables have essentially no impact on the large economy and the Small Economy exogenous variables are essentially excluded from the equations of the large economy variables.

**8.4. Identification.** The Excel sheet `Identification` can be used to specify a non-recursive identification of a structural VAR, see Figure 7 for a nearly recursive identification. The first column contains labels for the shocks, and the first row puts labels on the variables in the system. A zero in position  $(i, j)$  of the restriction matrix means that  $\Upsilon_{ij}$  (coefficient on variable  $j$  in equation  $i$ ) is forced to be zero, whereas a one means that the coefficient is unrestricted in the estimation. BayesVAR warns the user if the restrictions do not identify the system.

In addition to the identification restrictions in `Identification`, the user must specify a coefficient in each equation that will be used for normalization (restricted to be positive).

This is done in Options/StructuralVARs/Normalizing coefficients. There is also an option to use the automatic normalization rule in Waggoner and Zha (2003a).

**8.5. CondForecast.** BayesVAR can produce forecasts conditional on pre-specified paths for a subset of the endogenous variables. The Excel sheet **CondForecast** (see Figure 8 for an example in a seven-variable VAR) is made up of two parts. First, to the left in the sheet, the pre-specified paths for the conditioning variables are specified. The columns correspond to the endogenous variables, and the rows to different forecast horizons. An empty cell means that the variable is not subject to restrictions at that particular forecast horizon. In the example in Figure 8, the three foreign variables,  $yf$ ,  $pf$  and  $rf$  have pre-specified paths for quarter 1-3. The domestic interest rate  $r$  is assumed to be constant at 4 in the coming 6 quarters. Finally, the real exchange rate  $er$  is fixed to 10 during the first year.

BayesVAR uses the structural shocks (the  $\varepsilon$  in equation 2.2) during the forecasting period to produce these conditionings. BayesVAR allows the user to specify which subset of the shocks (e.g. the foreign shocks) that are used to fulfill the conditions of a certain subset of the conditioned endogenous variables (e.g. the foreign variables). This is specified in the right hand side of the CondForecast sheet. An example is probably the best way to explain these settings. In the example in Figure 8 there are three subsets of shocks:

- (1) The conditioning on the foreign variables,  $yf$ ,  $pf$  and  $rf$  are to be fulfilled by the first shock set (hence the ones in the columns to the right). Since there are three conditioning variables here, we need three shocks in the first shock set.
- (2) The condition on the domestic interest rate are to be fulfilled by the second shock set (hence the number 2 in the  $r$  column). We need a single shock in this shock set.
- (3) The condition on the real exchange rate ( $er$ ) are to be fulfilled by the third shock set (hence the number 3 in the  $r$  column). We need a single shock in this shock set.

BayesVAR now knows the subset of conditioning variables (1.  $yf, pf, rf$  2.  $r$  and 3.  $er$ ), their pre-specified paths and that it should use three shock sets to satisfy the restrictions on the conditioning variables. The only missing information is which of the seven structural shocks that belong to the first, second and third shock subset, respectively. This is specified in the Options sheet (*Forecasting Options/Constructive*

*shocks in conditional forecasts*). In this example we set this input to [1:3; 6; 7]. This defines the three shock subsets (separated by semicolon): 1.  $(\varepsilon_1, \varepsilon_2, \varepsilon_3)$ , 2.  $(\varepsilon_6)$  and 3.  $(\varepsilon_7)$ , where  $\varepsilon_j$  denotes the  $j$ th element of the structural shock vector  $\varepsilon$ . If a recursive identification has been used, then these shocks subset may be labeled foreign shocks, interest rate shock and exchange rate shock. With a non-recursive identification, then  $\varepsilon_6$  may be given a structural interpretation as a monetary policy shock. This way the conditional forecasts can be given a structural interpretation.

It is important to understand how BayesVAR uses the structural shocks to produce conditional forecasts. A conditional forecast at a given horizon  $h$  is computed as follows:

- The shocks that are not used to produce a conditioning at horizon  $h$  are either set to zero or drawn from their normal distributions (this is set by *Options/Forecasting Options/Non-constructive shocks* are drawn from distribution).
- The first shock set (labelled 1 in the *CondForecast* sheet) is now injected so that the first set of endogenous conditioning variables meet their conditions (conditional on the generated values for the non-constructive shocks).
- The second shock set is now injected so that the second set of endogenous conditioning variables meet their conditions (conditional on the values for the non-constructive shocks and the first shock set), and so on for all the shock sets.

It is apparent from the above description that the choice of conditioning variables and shock sets must respect the structure of the contemporaneous restrictions in  $\Upsilon$  (for example, a recursive identification on  $(yf, pf, rf, y, p, r, er)$  would be valid in the current example). BayesVAR will not check this, and the code will run even if the conditional forecasting inputs are incorrectly specified in this respect, but the forecast will not satisfy all the imposed conditions on the endogenous variables. Note also that the order of the shock sets matter, in the sense that the shock subsets later in the order must operate conditional on injected shocks in the subsets that come earlier in the order.

The conditioning paths for *Difference* variables (see Section 8.3 on *Difference variables*) can be specified as growth rates (see *Options/Forecasting Options/Conditioning paths for difference variables specified as annual growth*).

It is also possible in BayesVAR, for example, to let a variable be unrestricted at forecast horizons  $h = 1, 2, 3$  and 4, and then fix it to pre-specified values at  $h = 5$  and 6, and then finally let it be unrestricted again during the rest of the forecasting

period. This flexibility cannot be used when the conditioning paths are specified in annual growth rates for **Difference** variables.

## APPENDIX A. DETAILS OF THE OPTIONS SHEET

## DATA OPTIONS

## ENDOGENOUS VARIABLES

**Function:** A vector with variable indices to select modelled endogenous variables in the data base, see the Excel sheet **Endo**.

**Format:** Row vector .

**Example:** [1 3:4 7] fits a VAR with variable number 1, 3, 4, 5, 6 and 7 in the data base (**Endo** sheet) as endogenous variables in the VAR.

## EXOGENOUS VARIABLES

**Function:** A vector with variable indices to select the exogenous variables in the data base, see the Excel sheet **Exo**.

**Format:** Row vector.

**Example:** [1 3] uses variable numbered 1 and 3 in the data base (**Exo** sheet) as exogenous variables in the VAR.

## FIRST DATE OF ESTIMATION SAMPLE

**Function:** The date of the first observation in the estimation sample.

**Format:** String.

**Example:** 1980Q1.

**Note:** The VAR with  $K$  lags uses the first  $K$  observations in the sample as initial values for the lags.

## FIRST FORECAST DATE

**Function:** The date where the first sequential forecast is *produced*.

**Format:** String.

**Example:** 1995Q4.

**Note:** A forecast *produced* at 1995Q4 uses all data up to and including 1995Q4 to forecast the future values for 1996Q1, 1996Q2, ...

## LAST FORECAST DATE

**Function:** The date where the last sequential forecast is *produced*.

**Format:** String.

**Example:** 2002Q4.

**Note:** See FIRST FORECAST DATE.

## SEASONAL CYCLE

**Function:** The seasonality of the data.

**Format:** Scalar.

**Options:** 1 (Yearly), 4 (Quarterly), and 12 (Monthly).

**Example:** 4 for quarterly data.

## DETTRENDED VARIABLES

**Function:** A vector with variable indices of variables that are to be demeaned and detrended by the program.

**Format:** Row vector/String.

**Example:**[1 3:5], demeanes and detrends endogenous variables 1, 3, 4 and 5.

## MODEL AND PRIOR OPTIONS

## LAG LENGTH

**Function:** Lag length ( $K$ ) of the VAR.

**Format:** Positive integer.

**Example:** 4.

## CONSTANT

**Function:** Determines how the constant and deterministic terms enter the model.

**Format:** String.

**Options:** none (no constant), standard (constant and deterministic terms enter additively as in eq. 2.1) or meanadj (steady state VAR, constant and deterministic terms enter as in eq. 2.3).

**Example:** meanadj.

## OVERALL TIGHTNESS

**Function:** Prior overall tightness ( $\lambda_1$ , see Section 3) in the Litterman prior on the VAR coefficients.

**Format:** Positive scalar.

**Example:** 0.2.

## CROSS-VARIABLE TIGHTNESS

**Function:** Prior cross-variable tightness ( $\lambda_2$ , see Section 3) in the Litterman prior on the VAR coefficients.

**Format:** Scalar in  $(0, 1]$ .

**Example:** 0.5.

## LAG DECAY

**Function:** Prior lag decay ( $\lambda_3$ , see Section 3) in the Litterman prior on the VAR coefficients.

**Format:** Positive scalar.

**Example:** 1.

## EXOGENITY TIGHTNESS

**Function:** Prior exogeneity tightness ( $\lambda_4$ , see Section 3) in the Litterman prior on the VAR coefficients.

**Format:** Scalar in  $(0, 1]$ .

**Example:** 0.01.

**Note:** This prior shrinkage parameter can be used to incorporate the belief that small economies should not have a large influence on large economies.  $\lambda_4$  puts additional shrinkage toward zero for parameters that relates small economy variables to large economy variables. Variables are classified as large economy variables in the Excel sheet **Endoproperties**. By setting  $\lambda_4$  to a very small number we can enforce (essentially) exact block recursiveness. All model parameters are still simulated, but the zero-restricted block are always very close to zero.

## DETERMINISTIC TIGHTNESS

**Function:** Prior tightness on the deterministic variables ( $\lambda_5$ , see Section 3) in the Litterman prior on  $\Phi$ .

**Format:** Positive scalar.

**Example:** 100.

**Note:** This prior parameter only applies to the VAR on standard form (2.1). In the steady state VAR in (2.3), the prior on the deterministic coefficients ( $\Psi$ ) are specified directly in the Excel sheet `Exoproperties`.

#### SEASONAL TIGHTNESS

**Function:** Special handling of tightness on the seasonal variables ( $\lambda_6$ , see Section 3) in the Litterman prior on  $\Pi$ .

**Format:** Scalar in  $(0, 1]$ .

**Example:** 1.

**Note:** The Litterman prior makes the prior tighter around zero for longer lags. When data contains seasonality it may be preferable to handle the seasonal lags (lag 4, 8, 12, etc. for quarterly data) differently for the non-seasonal lags. The prior hyperparameter  $0 < \lambda_6 \leq 1$  can be used to control this. As an example, if  $\lambda_6 = 1$ , then lag 4 has the same prior standard deviation as lag 1, lag 8 has the same prior standard deviation as lag 2 etc.

#### LOAD PRIOR FROM FILE

**Function:** Determines if the Litterman prior is overridden by a user specified prior loaded from file 'ManualPrior.m'.

**Format:** yes / no.

**Note:** This file must contain the variables `mu_pi` and `Omega_pi` if a Steady State VAR is used. The prior is then  $\text{vec}(\Pi_1, \dots, \Pi_K)' \sim N(\mu_\pi, \Omega_\pi)$ . If a Standard VAR is used then the file must contain the variables `mu` and `Omega`, and then  $\text{vec}(\Pi_1, \dots, \Pi_K, \Phi)' \sim N(\mu, \Omega)$ .

### POSTERIOR SAMPLING OPTIONS

#### NUMBER OF DRAWS (POST BURN-IN) FROM POSTERIOR AND PREDICTIVE DISTRIBUTIONS

**Function:** The number of Gibbs sampling draws from posterior and predictive (forecast) distributions.

**Format:** Positive integer.

**Example:** 10000.

## LOAD PARAMETER AND PREDICTION DRAWS FROM FILE

**Function:** Posterior draws and simulated predictions can be loaded from file. This field should contain the name of file where the posterior draws and predictions are saved, excluding the YEAR\_PERIOD addendum which is produced by the code. See the example below.

**Format:** String.

**Example:** If predictions for two different forecast dates are stored in Example2002Q1.mat and Example2002Q2.mat, then this field should read 'Example'.

## COMPUTE LOG POSTERIOR FOR EACH DRAW

**Function:** Determines if the log posterior is computed for each draw. This is needed if the marginal likelihood is computed by the modified harmonic mean estimator in Geweke (1999).

**Format:** yes/no.

## METHOD FOR COMPUTING THE MARGINAL LIKELIHOOD

**Function:** Determines the method for computing the marginal likelihood.

**Format:** String.

**Options:** none, modharm (modified harmonic, Geweke (1999)) and chib (Chib, 1995).

**Note 1:** BayesVAR only computes Chib's estimate for the Steady State VAR (reduced form or recursive identification, but not for non-recursive identification).

**Note 2:** The variable NModHarmBatches in BayesVAR.m can be changed to have the modified harmonic estimates computed sequentially throughout the posterior draws. This is a good way to check if the marginal likelihood estimate has converged (the marginal likelihood estimate typically converges later than the posterior distribution). For example, by setting NModHarmBatches to 5, the marginal likelihood estimate is first computed using the first 20% of the draws, then using the first 40% of the draws and so on.

**Note 3:** The priors on  $\Sigma$  (reduced form) and  $\Upsilon$  (Structural form) in BayesVAR are improper (integrate to infinity over their domain). These priors are OK to use in estimation (the posterior is proper), but cannot be used for model comparison *unless* all compared models have the same restrictions on  $\Sigma$  or  $\Upsilon$ . Most model comparisons with VAR can therefore be done (different lag lengths, different exogenous variables, different

prior on  $\Pi$  etc.), but not comparisons where the structure of the  $\Sigma$  or  $\Upsilon$  varies across models.

#### MAXIMUM LIKELIHOOD

**Function:** Maximum likelihood estimates computed instead of Bayesian posteriors.

**Format:** String.

**Options:** none (Bayesian estimation), **unrestricted**, **blockFIML** (FIML on block-recursive system), **blockQuasi** (non-iterative quasi-ML on block-recursive system,  $\Sigma$  is estimated from an unrestricted system and then  $\Pi$  is estimated under block-recursiveness).

**Note:** When maximum likelihood is used, the VAR is estimated on standard form (maximum likelihood estimates are invariant to transformations, so this does not matter for forecasts etc.). ML standard errors are not computed by BayesVAR. The ML standard errors can be obtained from a Bayesian estimation with flat priors ( $\lambda_1$  large and  $\lambda_2 = \lambda_3 = \lambda_5 = \lambda_6 = 1$ ).

#### RESTRICT VAR TO BE STATIONARY

**Function:** Determines if the estimated VAR is restricted to be stationary.

**Format:** yes / no.

**Note:** This option only applies to Bayesian estimation, not maximum likelihood. Non-stationary Gibbs sampling draws are discarded.

#### PERCENTAGE DISCARDED BURN-IN POSTERIOR DRAWS

**Function:** This determines the percentage of posterior draws that are discarded as burn-in.

**Format:** Scalar in  $[0, 100)$ .

**Example:** 5.

#### THIN-OUT FREQUENCY FOR DRAWS OF IR, HIST. DECOMP. AND STRUCTURAL SHOCKS

**Function:** Determines how often posterior draws of IR etc. are stored. Does not affect draws of VAR parameters and forecasts.

**Format:** Positive integer  $< NIter$  (number of posterior draws).

**Example:** 1 (very draw is stored), 10 (every tenth draw is stored).

**Note:** Setting this number larger than one speeds up computations and reduces memory requirements. The drawback is that fewer draws are used to approximate the posterior

distribution of IRs etc. This loss of estimation precision may not be very large, however, because thinning out the posterior draws also reduces the autocorrelation in the draws.

## FORECASTING OPTIONS

### NUMBER OF PERIODS TO FORECAST

**Function:** Number of periods ahead to forecast (dynamic forecasts).

**Format:** Positive integer (zero allowed).

**Example:** 12.

### PLOT THE FORECASTS

**Function:** Determines whether or not point forecasts (posterior median) and forecast intervals are plotted.

**Format:** 0/1/2.

**Options:** 0 (no plotting), 1 (plot every year) or 2 (plot every period).

**Example:** 1.

### PLOT PREDICTIONS FOR VARIABLE

**Function:** Determines the subset of endogenous variables plotted in the prediction graphs.

**Format:** Row vector/string 'all' (plots all the variables in the system) or 'none'

**Options:** Row vector, all (plot all endogenous variables) or none (no plotting).

**Example:** [1 3:5 7]. Plots the forecasts for variables numbered 1, 3, 4, 5 and 7 in the data base.

### CONSTRUCTIVE SHOCKS IN CONDITIONAL FORECASTS

**Function:** Determines the subset of shocks that are constructive in the conditional forecasts. A shock is constructive if it is used to meet the restrictions on the endogenous variables in the conditional forecast.

**Format:** Semicolon-separated row vector/String.

**Options:** Semicolon-separated row vector / none (unconditional forecasts).

**Example:** [1 3; 4; 6:7]. This give the three distinct blocks of shocks i) 1 and 3, ii) 4 and iii) 6 and 7 to generate the conditions. Must match up with the info in the Excel sheet CondForecast, see Section 8.5.

## NON-CONSTRUCTIVE SHOCKS ARE DRAWN FROM DISTRIBUTION

**Function:** Determines if the non-constructive shocks (shocks not used to produce the conditioning on the endogenous variables) are drawn from their distribution or set to zero in the conditional forecasts.

**Format:** yes/no.

## HISTORICAL DECOMPOSITION OF SHOCKS

**Function:** The shocks for which the historical decomposition are computed.

**Format:** Semicolon-separated row vector/String.

**Options:** Semicolon-separated row vector / none (no decomposition).

**Example:** [1 3; 4] will graph actual data and historical pattern that would have occurred if i) only shocks 1 and 3 or ii) only shock 4 had hit the economy.

**Note:** The decomposition is always computed for the baseline scenario without any shocks. Shocks can be switched off during the whole estimation period or only from a certain time period and forward. See Adolfson, Andersson, Lindé, Vredin and Villani (in press) for an example.

## START SHUTTING DOWN HISTORICAL SHOCKS AT DATE

**Function:** The date when the shocks are shut down in the historical decomposition. See also the companion option HISTORICAL DECOMPOSITION OF SHOCKS above.

**Format:** String.

**Options:** Date string / first (shocks are shut down from first observation in estimation sample and onwards).

**Example:** 1995Q4.

**Note:** See Adolfson, Andersson, Lindé, Vredin and Villani (in press) for an example.

## VARIABLES TO PLOT IN THE HISTORICAL DECOMPOSITIONS

**Function:** Determines which variable are plotted in the historical decompositions.

**Format:** Row vector.

**Options:** Row vector / all

**Example:** [4 5 6]. Forecasts are plotted for variables 4, 5 and 6.

**Note:** See Adolfson, Andersson, Lindé, Vredin and Villani (in press) for an example.

## SCENARIOS TO PLOT IN THE HISTORICAL DECOMPOSITIONS

**Function:** Determines which scenarios are plotted in the historical decompositions.

**Format:** Row vector.

**Options:** Row vector / all

**Example:** [1 3]. Forecasts from scenario 1 and 3 are plotted.

**Note:** See Adolfson, Andersson, Lindé, Vredin and Villani (in press) for an example.

## FORECASTING EVALUATION OPTIONS

### FORECAST EVALUATION HORIZONS

**Function:** Forecast horizons where forecasts are evaluated.

**Format:** Row vector / Empty vector (no evaluation).

**Example:** [1:4 8 12 16]

### UNIVARIATE MEASURES OF POINT FORECAST ACCURACY

**Function:** Determines which accuracy measures are printed to file. If e.g. [1 2 3 4], all of RMSE, MAE, MAPE, MPE are printed.

**Format:** Row vector.

**Options:** 1 (RMSE, root mean squared error), 2 (MAE, mean absolute error), 3 (MAPE, mean absolute percentage error), 4 (MPE, mean percentage error).

**Example:** [1 4] computes and prints RMSE and MPE.

### NUMBER OF PAST OBSERVATIONS IN RECENT MEAN FORECAST

**Function:** This specifies the number  $r$  of past observations used in the construction of the RecentMean benchmark forecast (Section 2).

**Format:** Positive integer / Row vector.

**Example:** 12.

**Note:** This may be a row vector with one element for each sequential forecast date so that different number of past observations may be used at each forecasting period.

### VARIABLE SUBSETS FOR MULTIVARIATE MEASURES OF FORECAST ACCURACY

**Function:** The subsets for which the multivariate measures of point forecast accuracy (LogDetMSFE, trace MSFE, LPDS) are computed.

**Format:** Semicolon-separated row vector / none (no evaluation) / all (a single subset consisting of all endogenous variables).

**Example:** [1:7; 1; 1:3]. LogDetMSFE, TraceMSFE and LPDS are computed on the three subset of endogenous variables: i) 1, 2, 3..., 7, ii) 1, and iii) 1, 2, 3.

**Note:** See Adolfson, Lindé and Villani (2007) for more details.

#### SCALE MATRIX FOR TRACE OF MSFE MATRIX

**Function:** Determines the choice of scale matrix for the TraceMSFE measure.

**Format:** String.

**Options:** `stdev` (ScaleMatrix is a diagonal matrix with the diagonal elements equal to inverse of estimated standard deviations in past data, see also the next setting below.) / `identity` or `none` (Identity/no scaling) / `filename` (scale matrix is loaded from file 'filename.mat').

**Example:** `identity`.

**Note:** See Adolfson, Lindé and Villani (2007) for more details.

#### FIRST DATE FOR COMPUTING SCALE MATRIX FROM DATA

**Function:** If option `none` is chosen for the scale matrix, then scale matrix is set equal to the covariance matrix based on past data. This options sets the first date for this estimation sample.

**Format:** String.

**Example:** `1993Q1`.

#### VARIABLES IN FORECAST CASCADE PLOT

**Function:** Determines which variables are plotted in the cascade graph.

**Format:** Row vector / string

**Options:** `none` (no plotting), `all` (all variables plotted), `vector`.

**Example:** `[1 3 5]`, plots forecast cascades for variables 1, 3 and 5.

#### FORECAST CASCADES IN SEPARATE PLOTS FOR EACH VARIABLE

**Function:** Determines if variables in the forecast cascades are plotted in the same figure or one figure for each variable etc.

**Format:** 0/1/2.

**Options:** 0 (every variable in a separate figure), 1 (plot variables in multiple 2-by-2 subplots) or 2 (all variables in the same figure).

## OPTIONS FOR ASSESSING MODEL FIT

## PLOT RESIDUALS FOR VARIABLE

**Function:** Determines the set of variables that are plotted in the residual graphs.

**Format:** Row vector / string

**Options:** Row vector / none (no plotting) / all (all variables plotted).

**Example:** [1 3 5], plots residuals for variables 1, 3 and 5.

**Note:** Actual and fitted values of Difference variables are transformed to annual growth rates, but residuals are plotted in the form used in the estimation.

## COMPUTE FIT AND RESIDUALS BASED ON POSTERIOR MEDIAN ESTIMATES

**Function:** Determines if model fit and residuals are computed conditional on point estimates (posterior median) of the parameters or as a point estimate (median) in the posterior distribution of the model fit/residuals.

**Format:** yes/no

**Example:** yes, model fit and residual are computed conditional on point estimates of the parameters.

## PLOT ACTUAL VS FITTED (TIME SERIES PLOT)

**Function:** Time plot of actual data and fitted values.

**Format:** yes / no.

## PLOT ACTUAL VS FITTED (CROSSPLOT)

**Function:** Scatter plot of actual data vs fitted values.

**Format:** yes / no.

## PLOT ACTUAL RESIDUALS

**Function:** Plots unscaled residuals as a function of time.

**Format:** yes / no.

## PLOT RESIDUAL AUTOCORRELATION

**Function:** Determines the number of lags in the residual autocorrelogram.

**Format:** Positive integer (zero allowed).

**Example:** 12.

**Note:** If this is set to zero, then the autocorrelogram is not computed.

## PLOT RESIDUAL HISTOGRAMS

**Function:** Plots histograms of the residuals.

**Format:** yes / no.

## COMPUTING THE STEADY STATE

**Function:** Determines if the steady state (unconditional mean) of the process is computed.

**Format:** yes / no.

## PLOTTING STEADY STATE OVER TIME

**Function:** Determines if the steady states are plotted as a function of time. This only applies when sequential forecasts are made.

**Format:** yes / no.

## CONVERT FITTED VALUES OF DIFFERENCE VARIABLES TO ANNUAL GROWTH

**Function:** Determines if the fitted values of Difference variables are converted to annual growth rates.

**Format:** yes / no.

## OPTIONS FOR STRUCTURAL/IDENTIFIED VARS

## STRUCTURAL VAR IDENTIFICATION

**Function:** The form of restrictions on the contemporaneous parameters.

**Format:** String.

**Options:** none (reduced form) / recursive (Choleski, lower triangular) / non-recursive (general zero restrictions using the pattern of zeros in Identification sheet)

## NORMALIZING COEFFICIENTS

**Function:** Indices for simultaneous coefficients that are normalized to be positive.

**Format:** Vector / String.

**Options:** Row vector / NaN (Waggoner-Zha (2003a) normalization) / Empty Vector (Waggoner-Zha (2003a) normalization).

**Example:** [2 3]. In the bivariate system, the first equation is normalized on the second *unrestricted* coefficient, the second equation is normalized on the third unrestricted coefficient.

**Note:** The number of elements in the row vector input has to be equal to the number of equations in the system.

#### IR HORIZON

**Function:** The number of future time periods to plot in the impulse response functions.

**Format:** Positive integer.

**Example:** 16.

**Note:** The impulse responses are all plotted in the same figure. The function `SomeImpulse.m` can be used to plot the IRs from a single shock on selected subset of the variables in a separate figure. `BayesVAR.m` contains some commented lines that does this exercise (search for `SomeImpulse` in `BayesVAR.m` to find it).

#### CONVERT TO YEARLY GROWTH RATES IN IMPULSE RESPONSE FUNCTION

**Function:** Determines if the impulse responses for **Difference** variables are presented as yearly averages or in first differences.

**Format:** yes / no.

**Note:** For quarterly data, the three quarters before the shock are set to zero. For monthly data, the 11 quarters before the shock are set to zero.

#### DEGREES OF FREEDOM CORRECTION OF ML (RECURSIVE IDENTIFICATION)

**Function:** Determines whether or not to use the degrees of freedom correction of  $\Sigma$  in the ML estimation.

**Format:** yes / no.

#### FORECAST ERROR VARIANCE DECOMPOSITION

**Function:** Horizons were the Forecast Error Variance Decomposition are computed.

**Format:** Row Vector / String.

**Options:** Row vector / all (all horizons from 0 to the impulse response horizon) / none (no decomposition).

**Example:** [0 4 8 12], plot the Forecast Error Variance Decomposition at horizons 0, 4, 8, and 12.

**Note:** The Bayesian point estimates of the forecast error variance decompositions (FEVD) are medians over the posterior draws of the FEVDs. They need not sum to 100% for each variable. The mean of the FEVD distribution sums to one (the variable MeanFEVD contains the mean of the FEVD). The maximal FEVD horizon cannot exceed the IR horizon.

#### STORE AND PLOT POSTERIOR DRAWS OF STRUCTURAL SHOCKS

**Function:** Determines if posterior draw of structural shocks are stored and subsequently plotted as a function of time.

**Options:** yes / no.

#### MISC OPTIONS

##### SAVE RESULTS TO FILE

**Function:** Save predictions, posterior draws etc to a .mat file with the given name. The last estimation period will be added to the files' names.

**Format:** String.

**Example:** ExampleFile.

##### SAVE POSTERIOR SAMPLE OF PARAMETERS

**Function:** Save posterior draws to file?

**Format:** yes / no.

##### PRINT ESTIMATION SUMMARY TO FILE

**Function:** Print point estimates, standard deviation and Bayesian  $t$ -ratios to txt-file.

**Format:** yes / no.

**Note:** This file should open in automatically in Windows Notepad.

##### LENGTH OF PAST IN PREDICTION PLOTS

**Function:** The number of historical data points plotted before the predictions in the graphs.

**Format:** Positive Integer.

**Example:** 12.

### HIGHEST POSTERIOR DENSITY (HPD) PREDICTION INTERVALS

**Function:** Determines if HPD intervals are to be computed.

**Format:** yes / no.

**Options:** yes (HPD) / no (equal tailed intervals)

**Note:** HPD intervals are time-consuming.

### COVERAGE PROBABILITY OF PRIOR INTERVALS FOR DETERMINISTIC COMPONENTS

**Function:** Coverage probability for the specified prior interval in the mean adjusted form (only relevant if `constant=meanadj`). See Excel sheet `Endoproperties`.

**Format:** Scalar in (0, 1).

**Example:** 0.95 means that prior probability intervals specified for  $\Psi$  in `Endoproperties` sheet are 95% intervals.

### COVERAGE PROBABILITY OF FORECAST/IR/FEVD BANDS

**Function:** Row vector which may contain up to three coverage probabilities for uncertainty bands.

**Format:** Row Vector.

**Example:** [0.5 0.75 0.95] would display 50%, 75% and 95% probability bands for impulse responses and predictions.

**Note:** The colors of the uncertainty bands may be changed in `PredSummary.m` (forecasts) or `ImpulseSummary` (IRs). Change the colormap matrix `colorband` under `USER INPUT` in the code.

### LOOP ON QUANTITY

**Function:** The program can repeat **all** the computations for different values of certain key parameters (e.g. lag length). This input determines the quantity that is looped over.

**Options:** none / `LagLength` / `lambda1` / `lambda2` / `lambda3` / `lambda4` / `lambda5` / `lambda6`.

**Example:** `lambda2`.

**Note:** This is very useful for sensitivity analysis. E.g. how would the out-of-sample forecast performance change if  $\lambda_1$  was set to another value?

## LOOP OVER VALUES

**Function:** This determines the set of values on which LOOPQUANTITY loops over.

**Format:** Row vector.

**Example:** [1:5]. If LOOPQUANTITY is set to LagLength, then the program repeats **all** computations for lag length  $K = 1, 2, \dots, 5$ .

## PLOT AND PRINT AT EVERY SEQUENTIAL FORECAST DATE

**Function:** If yes, then plots and print-outs are produced at every forecast date, always according to the other options. If no, only plots and prints at the final estimation date and most other inputs are overridden at the sequential forecast dates. Forecast are plotted even if this option is set to no, but most of the model diagnostics (residual plots, impulse responses etc) are only plotted at the final forecast date.

**Format:** yes / no.

## RANDOM NUMBER GENERATOR SEED

**Function:** Sets the seed of the random number generator.

**Format:** String/Scalar.

**Options:** random (seed is set randomly using the CPU clock) or a scalar.

**Example:** 1223.

## REFERENCES

- [1] Adolfson, M., Lindé, J. and Villani, M. (2007). FORECASTING PERFORMANCE OF AN OPEN ECONOMY DSGE MODEL, *Econometric Reviews*, **26**, 289-328. Available at: [www.riksbank.com/research/villani](http://www.riksbank.com/research/villani).
- [2] Adolfson, M., Andersson, M. K., Lindé, J., Villani, M. and Vredin, A. (in press). MODERN FORECASTING MODELS IN ACTION: IMPROVING MACROECONOMIC ANALYSES AT CENTRAL BANKS. Forthcoming in *International Journal of Central Banking*. Available at: [www.riksbank.com/research/villani](http://www.riksbank.com/research/villani).
- [3] Chib, S. (1995). MARGINAL LIKELIHOOD FROM THE GIBBS OUTPUT, *Journal of the American Statistical Association*, **90**, 1313-21.
- [4] Doan, Thomas (1992), RATS USERS MANUAL, Version 4, Evanston, IL.
- [5] Geweke, John (1999). Using Simulation Methods for Bayesian Econometrics Models: Inference, Development and Communication, *Econometric Reviews*, **18**, 1-73.
- [6] Kadiyala, R. and Karlsson, S. (1997). NUMERICAL METHODS FOR ESTIMATION AND INFERENCE IN BAYESIAN VAR-MODELS, *Journal of Applied Econometrics* **12**, 99-132.
- [7] Litterman, R. B. (1986). FORECASTING WITH BAYESIAN VECTOR AUTOREGRESSIONS - FIVE YEARS OF EXPERIENCE, *Journal of Business and Economic Statistics*, **5**, 25-38.
- [8] Villani, M. (2007). STEADY STATE PRIORS FOR VECTOR AUTOREGRESSIONS. Sveriges Riksbank Working Paper Series No. 181. Available at: [www.riksbank.com/research/villani](http://www.riksbank.com/research/villani).
- [9] Waggoner, D. F. and Zha, T. (2003a). LIKELIHOOD-PRESERVING NORMALIZATION IN MULTIPLE EQUATION MODELS, *Journal of Econometrics*, **114**, 329-347.
- [10] Waggoner, D. F. and Zha, T. (2003b). A GIBBS SAMPLER FOR STRUCTURAL VECTOR AUTOREGRESSIONS, *Journal of Economic Dynamics and Control*, **28**, 349-366.

	A	B	C	D	E	F	G	H	I	J
1	<b>Data Options</b>		<i>Choice</i>		<i>Comment</i>					
2	Endogenous variables		[1 3 5]		Endogenous variables' indices in the data base. See the 'endo' sheet					
3	Exogenous variables		[1]		Exogenous variables' indices in the data base. See the 'dummy' sheet					
4	First date of estimation sample		1980Q2		Beginning date for data used in estimation. Note: the first K observations are used for to initialize VAR.					
5	First forecast date		2005Q4		Date of the first the sequential forecast. Note: this is the period where the forecast is made.					
6	Last forecast date		2005Q4		Date of the last the sequential forecast. Note: this is the period where the forecast is made.					
7	Seasonal cycle		4		The number time periods in a complete seasonal cycle. For quarterly data this is 4. Other frequencies only partially I					
8	Detrended variables		none		A vector with variable indices of variables that are to be demeaned and detrended by the program, e.g. [4 8]. If 'none'					
9										
10										
11										
12										
13	<b>Model and Prior Options</b>									
14	Lag length		4		Lag length of the VAR					
15	Constant		meanadj		Determines the parametrization of the deterministic term in the VAR. Options: 'none' (no constant), 'standard' (the u					
16	Overall tightness		0,2		Prior hyperparameter. Just like in the original Minnesota prior.					
17	Cross-variable tightness		0,5		Prior hyperparameter. Just like in the original Minnesota prior.					
18	Lag decay		1		Prior hyperparameter. Just like in the original Minnesota prior.					
19	Exogenity tightness		0,001		Prior hyperparameter. Domain: [0,1]. If =1, exogenous variables are treated just like the endogenous.					
20	Deterministic tightness		10		Prior hyperparameter. Prior standard deviation on the coefficients of the deterministic component. Applies only whe					
21	Seasonal tightness		nan		Prior hyperparameter. Domain: [0,1]. If =1, the first seasonal lag is shrunk just like the first lag etc. If this is 'nan', the					
22										
23										
24	<b>Posterior Sampling Options</b>									
25	Number of draws (post burn-in) from posterior and predictive distributions		1000		Note: No burn-in is removed from the posterior sample					
26	Load parameter and prediction draws from file		none		Name of file where the posterior draws and predictions are saved, excluding the YEAR_PERIOD addendum which					
27	Compute log posterior for each draw		yes		Must be 'yes' if marginal likelihood is computed by modified harmonic estimator					
28	Method for computing the marginal likelihood		modharm		Options: 'none', 'modharm' or 'chib'.					
29	Maximum likelihood		none		Maximum likelihood estimates computed instead of Bayesian posteriors. Options: 'none', 'unrestricted', 'blockFIML'.					
30	Restrict VAR to be stationary		yes		Only applies for Bayesian estimation. Non-stationary draw are discarded.					
31	Percentage discarded burn-in posterior draws		5		The percentage of posterior draws to discard as burn in					
32	Thin-out frequency for draws of IR, hist. decomp, residuals and shocks.		5		This determines how often posterior draws of IR etc are stored. Ex. if =1, every draw is stored, if =10, every tenth dr					
33										
34	<b>Forecasting Options</b>									
35	Number of periods to forecast		12							
36	Plot the forecasts		1		if 0, no plotting. if =1, plots every year, if =2, plots every period					
37	Plot predictions for variable		all		Determines which variables are plotted in the prediction graph. Ex [1 3 5], 'all' (plots all the variables in the system)					
38	Constructive shocks in conditional forecasts		[1;5]		List the shock indices which are to be used in the conditional forecasting. E.g. [1 3; 4] uses the two distinct blocks					
39	Non-constructive shocks are drawn from distribution		yes							
40	Historical decomposition of shocks		[1;3;5]		List the shock indices for which the decomposition is computed, e.g. [1 3; 4] will graph actual data and historical p					
41	Start shutting down historical shocks at date		1995Q1		if 'first', first date of the sample is used.					
42	Variables to plot in the historical decompositions		all		Row vector or 'all'					
43	Scenarios to plot in the historical decompositions		all		Row vector or 'all'					
44	Conditioning paths for difference variables specified as annual growth		yes							

FIGURE 1. First half of the Options sheet in the BayesVAR Excel workbook.

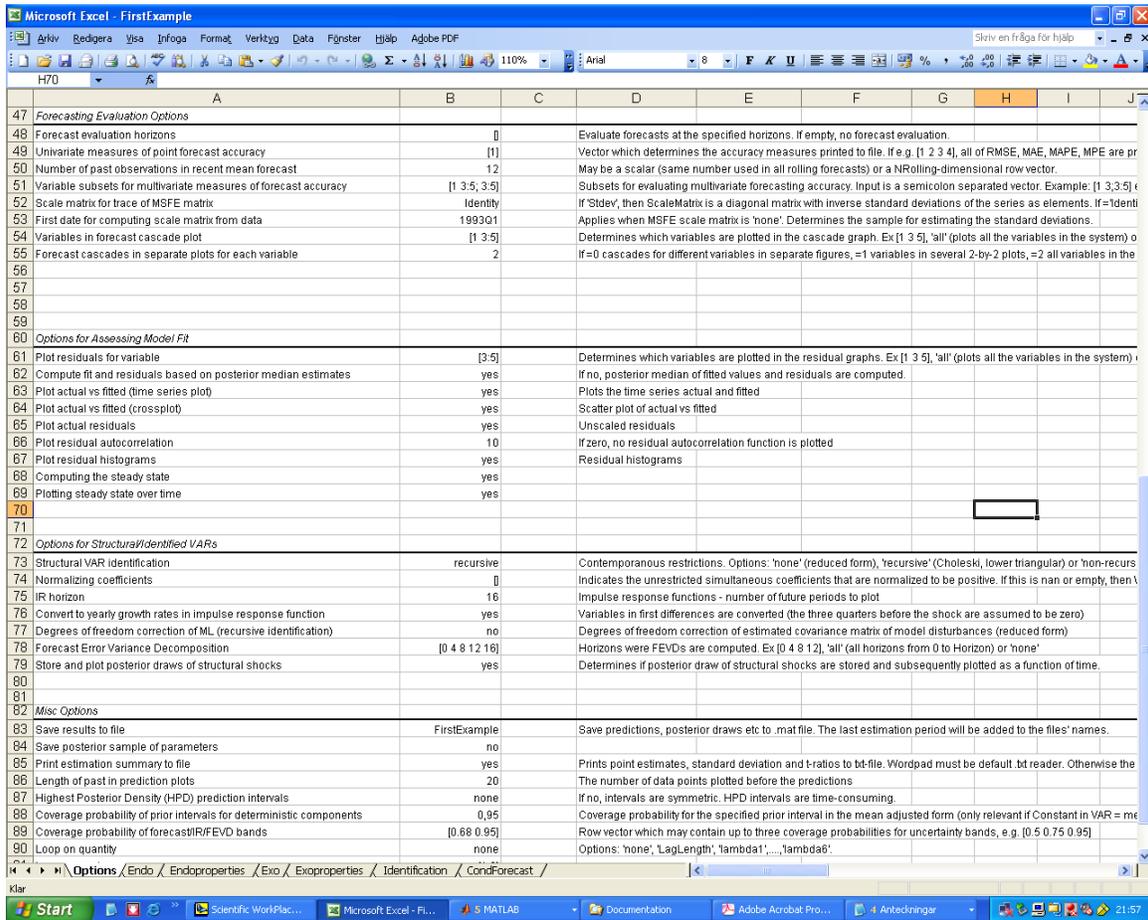


FIGURE 2. Second half of the Options sheet in the BayesVAR Excel workbook.

	A	B	C	D	E	F	G	H	I	J
1		yf	rf	y	pi	r				
2	jun-80	-1,016	12,7255	-0,7694	2,4316	12,1				
3	sep-80	0,1108	12,5085	0,2393	2,95223	12,1667				
4	dec-80	0,3493	12,4858	0,0072	3,7301	12,5333				
5	mar-81	0,2288	13,3739	-0,0578	3,48	15,2				
6	jun-81	0,1293	14,859	0,2855	2,67835	15,3				
7	sep-81	0,6115	17,4322	-0,0861	2,61445	13,4333				
8	dec-81	0,0921	13,8099	-0,0834	1,19713	13,4833				
9	mar-82	-0,143	13,7207	0,5495	2,48543	12,97				
10	jun-82	0,4124	13,5404	0,4702	2,18255	13,93				
11	sep-82	-0,2162	11,9593	-0,1043	1,94803	14,53				
12	dec-82	0,1875	11,3739	0,5311	2,22958	11,7367				
13	mar-83	0,8118	10,206	-0,1508	2,11928	9,7667				
14	jun-83	0,9981	8,8187	0,7512	2,01898	11				
15	sep-83	0,6469	9,2963	1,1056	2,52323	10,8067				
16	dec-83	1,1765	9,1408	1,2769	1,92693	11,84				
17	mar-84	1,3186	9,3082	1,9278	1,66473	10,7367				
18	jun-84	-0,2167	9,1126	0,278	2,13273	10,83				
19	sep-84	1,0788	9,1397	0,8764	1,62498	13,4733				
20	dec-84	0,7538	8,5736	0,81	1,90785	12,0267				
21	mar-85	0,7479	9,0136	0,0396	2,17715	12,5267				
22	jun-85	0,8223	8,4677	0,8547	2,02293	15,1667				
23	sep-85	1,0442	8,0477	0,7307	0,78183	15				
24	dec-85	0,6272	8,228	0,29	1,32455	13,0633				
25	mar-86	0,3046	8,9025	1,3563	1,02273	11,7333				
26	jun-86	1,2386	6,8343	0,2583	0,60698	11				
27	sep-86	0,6614	6,6552	0,5249	1,01983	8,73				

FIGURE 3. The Endo sheet in the BayesVAR Excel workbook.

	A	B	C	D	E	F	G	H	I	J
1		RegimeShift								
2	jun-80	1								
3	sep-80	1								
4	dec-80	1								
5	mar-81	1								
6	jun-81	1								
7	sep-81	1								
8	dec-81	1								
9	mar-82	1								
10	jun-82	1								
11	sep-82	1								
12	dec-82	1								
13	mar-83	1								
14	jun-83	1								
15	sep-83	1								
16	dec-83	1								
17	mar-84	1								
18	jun-84	1								
19	sep-84	1								
20	dec-84	1								
21	mar-85	1								
22	jun-85	1								
23	sep-85	1								
24	dec-85	1								
25	mar-86	1								
26	jun-86	1								

FIGURE 4. The Exo sheet in the BayesVAR Excel workbook.

	A	B	C	D	E	F	G	H	I	J
1	Variable	Large economy	Difference	Mean on First Lag	Seasonal	Constant_L	Constant_U	RegimeShift_L	RegimeShift_U	
2	yf	1	1	0	0	2	3	-1	1	
3	rf	1	0	0,9	0	4,5	5,5	1,5	2,5	
4	y	0	1	0	0	2	2,5	-1	1	
5	pi	0	1	0	0	1,7	2,3	4,3	5,7	
6	r	0	0	0,9	0	4	4,5	3	5,5	
7										
8										
9										
10										
11										
12										
13										
14										
15										
16										
17										
18										
19										
20										
21										
22										
23										
24										
25										
26										
27										
28										
29										
30										
31										
32										
33										
34										
35										
36										
37										
38										

FIGURE 5. The Endoproperties sheet in the BayesVAR Excel workbook.

	A	B	C	D	E	F	G
1	Dummy	Domestic					
2	RegimeShift	0					
3							
4							
5							
6							
7							
8							
9							
10							
11							
12							
13							
14							
15							
16							
17							
18							
19							

FIGURE 6. The Exoproperties sheet in the BayesVAR Excel workbook.

The screenshot shows the 'Identification' sheet in an Excel workbook. The data is organized as follows:

	A	B	C	D	E	F	G	H
1		yf	rf	y	pi	r		
2	yfShock	1	0	0	0	0		
3	mpfShock	1	1	0	0	0		
4	yShock	1	1	1	0	0		
5	piShock	1	1	1	1	0		
6	mpShock	0	1	0	1	1		
7								
8								
9								
10								
11								
12								
13								
14								
15								
16								
17								
18								
19								
20								
21								
22								

FIGURE 7. The Identification sheet in the BayesVAR Excel workbook.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Horizon	yf	pif	rf	y	pi	r	er		Horizon	yf	pif	rf	y	pi	r	er	
2	1	3,00	2,5	3			4,00	10		1	1	1	1			2	3	
3	2	3,50	2,5	3			4,00	10		2	1	1	1			2	3	
4	3	4,00	2,5	3			4,00	10		3	1	1	1			2	3	
5	4						4,00	10		4						2	3	
6	5						4,00			5						2		
7	6						4,00			6						2		
8	7									7						2		
9	8									8								

FIGURE 8. The CondForecast sheet in the BayesVAR Excel workbook.