Chapter 1

Econometric Modeling of the Relationship Among Macroeconomic Variables of Thailand: Bayesian VARs Model

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Bayesian VARs are very useful for making an analysis on uncertainty contemporaneous restrictions that contain many variables of macroeconomic. We used quarterly data set on macroeconomic variables which were collected from 1997Q2 to2011Q2. ADF-test to show that the results of all variables are integrated order zero I(0). Moreover, to investigate lag length, LR- test statistic to indicate of variable in systems is lag 2. We consider the varying set of hyper-parameters that coincides in the Bayesian VARs model. The best fitted model that to our belief in hyper-parameters is stationary or large standard deviation around the first lag coefficient and more weight on the sum of autoreressive coefficients component. In an analytical impulse response, we found that the shock effect to investment rate is a major shock problem for this system.

1. Introduction

Our paper investigates the structural VAR of output, unemployment rate, inflation, investment, and interest rates in Thailand, as well as on the analytical of impulse response for describing the movement of macroeconomic variable when it occurs as a shock to the system. Moreover, we use the Bayesian VAR model because assists us in using a few data set in the VARs model that is faced in the degree of freedom problem. Thus, the analysis of forecast and impulse response can be more accurate with direction and coefficient. We evaluate forecasting accuracy and perform a structural exercise on the economy of Thailand. We compare the vary hyper-parameters that is to our belief of prior in the Bayesian VAR model.

We separate this paper into two parts. First, we consider which set of hyper-parameter is appropriate by basing it on the log marginal data density and root mean square error (RMSE) of forecasting. After that, comparison is made with the recursive and non-recursive in coefficients for contemporaneous. This is followed with an estimation and analysis to the impulse response in the macroeconomic system.

The paper is organized as the following:

- In Section 1 we describe the priors for the baseline Bayesian VAR model.
- In Section 2 we perform the forecast evaluation for all the specifications.
- In Section 3 describe the data set, and in Section 4 the structural analysis on the macroeconomic

2. Literature review

Vector Autoregressions (VAR) are the traditional tools in macroeconomics which are used for structural analysis and forecasting. However, structural models do not impose restrictions on the parameters and provide a very general to capture complex data relationships.This provides a risk of over-parametrization due to the typical sample size available for macroeconomic variables. The number of unrestricted parameters that can be estimated, is rather limited. Consequently, VAR applications are usually based on a small number of variables.

The size of the VARs used in empirical applications ranges from about three to ten variables. This creates an omitted variable bias. So, both consequences for structural analysis and for forecasting are not accurate. In addition, the size limitation is a problem for applications that has a larger set of variables. For VAR literature, the solution to analyse whether data sets large or less is to define a core set of variables and add one variable. With this approach, the comparison of impulse responses between the models is difficult to justify. To solve these problems, recent literatures have proposed methods to impose restrictions on the covariance structure, such as limiting the number of parameters to estimate.

In this paper, we show that by applying Bayesian VARs (BSVAR) shrinkage, we are able to handle a large unrestricted amount of VARs. Therefore, a VAR framework can be applied to empirical studies that analyse many variables of time series. Thus, we can analyse structure VARs that contain many variables of macroeconomic. Consequently, Bayesian VAR is a valid alternative to analysis of large dynamic systems. We use the proposals made by Doan, Litterman, and Sims (1984) and Litterman (1986a). Litterman (1986a) found that applying Bayesian shrinkage in the VAR that contain a six variables can forecast performance much better. This suggests that overparametrization can already become appropriate systems for a model size and that shrinkage is a potential solution to this problem. However, although Litterman's priors are a traditional standard tool in applied macro (Leeper, Sims, and Zha, 1996; Sims and Zha, 1998; Robertson and Tallman, 1999), the imposition of priors has not been considered sufficient to deal with the larger models.

3. Methodology

3.1 Bayesian VARs

In this section, the various forecasting procedures used in our study are presented and discussed.

3.1.1 The Sims VAR method

Sims (1980) recommended the VAR models as an efficient method to verify causal relationships in economic variables and to forecast their evolution. On the theoretical level, this approach has its foundation in the work of Box and Jenkins (1980) and Tiao and Box (1981). The VAR(p) model can be written as

$$y_t = a_0 + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t \tag{1}$$

Let y_t is matrix $MT \times 1$ that is the vector of variables which have T observations on each dependent variables. The classical VAR model explains each variable by its own lag p and other variables lag p of all. Where A_j are $M \times M$ matrix of coefficients. And, a_0 is the deterministic component that included a constant and seasonal dummies. While ε_t is white noise processes of a zero-mean vector with positive definite contemporaneous covariance matrix Σ and zero covariance matrices at all other lags. In general form, Y is defined to $T \times M$ matrix which have T observations on each dependent variable in columns. ε and E denote the errors in y_t and Y, respectively. So, let $x_t = \left(1, y'_{t-1}, ..., y'_{t-p}\right)$ and

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix} \quad (2)$$

Setting $K = 1 + Mp$ be the number of coefficients in each equation of the VAR. Then X is a $T \times K$ matrix and $A = \left(a_0, A_1, ..., A_p\right)'$. Moreover, we define $\alpha = vec\left(A\right)$ is a matrix $KM \times 1$ such that vector contain all VAR coefficients. VAR can be written as:

$$Y = XA + E \quad (3)$$

or

$$y = (I_M \otimes X)\alpha + \varepsilon \quad (4)$$

Where $\varepsilon \sim N\left(0, \Sigma \otimes I_T\right)$. To derived the likelihood function, it can be calculated from the sampling density, $p\left(y \mid \alpha, \Sigma\right)$. It can be separated into two parts when it is a function of the parameters. One a distribution for α given Σ and another where Σ^{-1} has a Wishart distribution. That is,

$$\alpha \mid \Sigma, y \sim N\left(\hat{\alpha}, \Sigma \otimes \left(X'X\right)^{-1}\right) \quad (5)$$

and

$$\Sigma^{-1} \mid y \sim W\left(S^{-1}, T - K - M - 1\right) \quad (6)$$

where $\hat{A} = \left(X'X\right)^{-1} X'Y$ is the OLS estimate of A and $\hat{\alpha} = vec\left(\hat{A}\right)$ and

$$S = \left(Y - X\hat{A}\right)'\left(Y - X\hat{A}\right)$$

3.1.2 Normal-Wishart Prior

Koop and Korobilis (2010) said that 'the natural conjugate prior assumes each equation have the same explanatory variables and restriction of prior covariance of the coefficients in any two equations that is proportional to one another'. So, posterior simulation algorithms such as the Gibbs sample is required to Bayesian inference in models. Normal of $\alpha \mid \Sigma$ and Σ^{-1} being Wishart had being in the natural conjugate prior. Moreover, α and Σ are not independent if setting the prior for α depends on Σ. For this part we used independent of one another prior in VAR coefficients and the error covariance: name is "independent Normal-Wishart prior".

For setting different equations in the VAR have different explanatory variables, we defined the previous form in new term. Instead of α, let β are be as the VAR coefficients in restricted VAR model. Then, we rewrite each equation of VAR as

$$y_{mt} = z'_{mt}\beta_m + \varepsilon_{mt}$$

where $t = 1,...,T$ is observations for $m = 1,...,M$ variables. And, y_{mt} is the t^{th} observation on the m^{th} variable, z_{mt} is a k_m vector containing the t^{th} observation of the vector of explanatory variables relevant for the m^{th} variable and β_m is the k_m vector of coefficients. If $z_{mt} = \left(1, y'_{t-1},..., y'_{t-p}\right)'$ for $m = 1,...,M$ then it is the unrestricted VAR of the previous section. However, when allowing z_{mt} to vary across equations that mean allowing for the possibility of a restricted VAR. In other word, it restricted some of the coefficients on the lagged dependent variables to be zero).

We rewrite all equations into vectors and equations as $y_t = \left(y_{1t},..., y_{Mt}\right)'$, $\varepsilon_t = \left(\varepsilon_{1t},...,\varepsilon_{Mt}\right)'$,

$$\beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_M \end{pmatrix}$$

$$Z_t = \begin{pmatrix} z'_{1t} & 0 & \cdots & 0 \\ 0 & z'_{2t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & z'_{Mt} \end{pmatrix}$$

Where β is a $k \times 1$ vector and Z_t is $M \times k$, and $k = \sum_{j=1}^{M} k_j$. Assume ε_t to be i.i.d. $N(0, \Sigma)$. Then, we can write the VAR as

$$y = Z\beta + \varepsilon \tag{7}$$

where

$$y = \begin{pmatrix} y_1 \\ \vdots \\ y_T \end{pmatrix}$$

$$\varepsilon = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_T \end{pmatrix}$$

$$Z = \begin{pmatrix} Z_1 \\ \vdots \\ Z_T \end{pmatrix}$$

And $\varepsilon \sim N(0, I \otimes \Sigma)$. The independent Normal-Wishart prior for this model is.

$$p(\beta, \Sigma^{-1}) = p(\beta)\, p(\Sigma^{-1})$$

Where

$$\beta \sim N(\underline{\beta}, \underline{V}_\beta) \tag{8}$$

And

$$\Sigma^{-1} \sim W(\underline{S}^{-1}, \underline{v}) \tag{9}$$

Thus, the prior covariance matrix, $\underline{V}_\beta$ can be anything that we chooses. For instance, we could set $\underline{\beta}$ and $\underline{V}_\beta$ from the Minnesota prior. Setting $\underline{v} = \underline{S} = \underline{V}_\beta^{-1} = 0$ for non-informative prior.

Using this prior, calculating the joint posterior $p\left(\beta,\Sigma^{-1} \mid y\right)$does not a convenient form. So, we would allow easy Bayesian analysis. However, the conditional posterior distributions $p\left(\beta \mid \Sigma^{-1}, y\right)$and $p\left(\Sigma^{-1} \mid y,\beta\right)$ have convenient forms.

$$\beta \mid y,\Sigma^{-1} \sim N\left(\overline{\beta},\overline{V}_{\beta}\right) \quad (10)$$

Where

$$\overline{V}_{\beta} = \left(\underline{V}_{\beta}^{-1} + \sum_{t=1}^{T} Z_t'\Sigma^{-1}Z_t\right)^{-1}$$

And

$$\overline{\beta} = \overline{V}_{\beta}\left(\underline{V}_{\beta}^{-1}\underline{\beta} + \sum_{t=1}^{T} Z_t'\Sigma^{-1}y_t\right)$$

Furthermore,

$$\Sigma^{-1} \mid y,\beta \sim W\left(\overline{S}^{-1},\overline{v}\right) \quad (11)$$

Where

$$\overline{v} = T + \underline{v}$$

And

$$\overline{S} = \underline{S} + \sum_{t=1}^{T}\left(y_t - Z_t\beta\right)\left(y_t - Z_t\beta\right)'$$

Accordingly, a Gibbs sampler can be drawn for the Normal $p\left(\beta \mid y,\Sigma\right)$and the Wishart $p\left(\Sigma^{-1} \mid y,\beta\right)$. Then, calculating of posterior properties of parameters, marginal likelihoods and prediction can be done by the resulting posterior simulation.

3.1.3 BSVAR model

Sims and Zha (1998) and Waggoner and Zha (2003) and Brandt and Freeman (2006) suggested the estimated Bayesian structural VAR (BSVAR) model. This BSVAR model is based on a dynamic simultaneous equation model. The prior is be set for the structural parameters. Waggoner and Zha (2003) suggested the basic SVAR model as:

$$y_t' A_0 = \sum_{l=1}^{p} Y_{t-l}' A_l + z_t' D + \varepsilon_t' \quad , t = 1, ..., T \tag{12}$$

where parameter matrices A_i are $m \times m$ that is the contemporaneous and lagged effects of the endogenous variables. For an intercept term D is an $h \times m$ parameter matrix. Let y_t is the $m \times 1$ matrix of the endogenous variables, z_t is a $h \times 1$ vector of exogenous variables and ε_t is the $m \times 1$ matrix of structural shocks. The structural shocks have normal with mean and variance equal that is:

$$\begin{aligned} E\left[\varepsilon_t \mid y_1, ..., y_{t-1}, z_1, ..., z_{t-1}\right] &= 0 \\ E\left[\varepsilon_t \varepsilon_t' \mid y_1, ..., y_{t-1}, z_1, ..., z_{t-1}\right] &= I \end{aligned} \tag{13}$$

Let A_0 be the coefficients for the contemporaneous relationships among the variables. These describes the interrelated among the variables to each other in each time period. Existing outside of relationships of in the past quarter are described by the A_l lag coefficients. We assume non-singular matrix in the contemporaneous coefficient matrix for the structural model. Restrictions on elements respective variables of A_0 be zero imply to unrelated contemporaneously. The reduced form of the SVAR model can be found by post-multiplying through by A_0^{-1} that is:

$$\begin{aligned} y_t' A_0 A_0^{-1} &= \sum_{l=1}^{p} Y_{t-l}' A_l A_0^{-1} + z_t' D A_0^{-1} + \varepsilon_t' A_0^{-1} \\ y_t' &= \sum_{l=1}^{p} Y_{t-l}' B_l + z_t' \Gamma + \varepsilon_t' A_0^{-1} \end{aligned} \tag{14}$$

The cross-product of the reduced form innovations stand for the error covariance matrix that is:

$$. \; \Sigma = E\left[\left(\varepsilon_t' A_0^{-1}\right)\left(\varepsilon_t' A_0^{-1}\right)'\right] = \left[A_0 A_0'\right]^{-1} \tag{15}$$

When specification of the identity matrix for express meaning of the restrictions on the contemporaneous parameters in A_0 implied to the shocks "hit" each equation in the contemporaneous specification. For instance, if identity matrix is defined as in the following table,

	Equations		
Variables	*Eqn*1	*Eqn*2	*Eqn*3
Var.1	1	0	0
Var.2	1	1	0
Var.3	0	1	1

Then, the restriction of corresponding A_0 is:

	Equations		
Variables	*Eqn*1	*Eqn*2	*Eqn*3
Var.1	a_{11}	0	0
Var.2	a_{21}	a_{22}	0
Var.3	0	a_{23}	a_{33}

This setting interpreted as shocks in variables 1 and 2 hit equation 1 (the first column); shocks in variables 2 and 3 hit the second equation (column 2); and, shocks in variable 3 hit the third equation (column 3). In general, the reduced form A_0^{-1} is be set as a recursive that is just-identified triangular matrix (via a Cholesky decomposition of Σ), implied to contemporaneous causal chain among the equations. We used a maximum likelihood method to estimate the reduced form parameters of the model.

Blanchard and Quah (1989), Bernanke (1986), Sims (1986) suggested for SVARs, if we set the A_0 be non-recursive and over-identified. Therefore, the estimation should be used a maximum likelihood procedure to estimate the non-recursive contemporaneous relationships in the parameters of A_0. Such that this method used the reduced form residual covariance Σ to estimates of the elements of A_0.

In estimation of Bayesian approaches, the reduced form covariance Σ has $\left[m\times(m+1)\right]/2$ free parameters. Thus, A_0 can have no more than $\left[m\times(m+1)\right]/2$ free parameters. Models are called over-identified when A_0 has less than $\left[m\times(m+1)\right]/2$ free parameters or, equivalent or more than $\left[m\times(m+1)\right]/2$ zero restrictions,.

Sims and Zha (1998) and Waggoner and Zha (2003) suggested the prior for the model for each equations. To illustrate the prior in the model by setting

$$y_t' A_0 = x_t' F + \varepsilon_t' \quad (16)$$

Where,

$$x_t' = \left[y_{t-1}' \ldots y_{t-p}', z_t' \right], F' = \left[A_1' \ldots A_p' D' \right]$$

are the variables matrices and the coefficients for the SVAR model.

The general form of this prior is:

$$a_i \sim N\left(0, \bar{S}_i\right) \textit{ and } f_i \mid a_i \sim N\left(\bar{P}_i a_i, \bar{H}_i\right) \quad (17)$$

Where, $\bar{S}_i$ is a $m \times m$ prior covariance of the contemporaneous parameters, and $\bar{H}_i$ is the $k \times k$ prior covariance of the parameters in $f_i \mid a_i$. The prior means of a_i are zero in the structural model, while the "random walk" component is in $\bar{P}_i a_i$. Waggoner and Zha (2003) discussed ‘the Bayesian prior is constructed for the unrestricted VAR model and then mapped into the restricted prior parameter space’.

Sims-Zha (1998) suggested the prior parameterizes that we beliefs about the conditional mean of the coefficients of the lagged effects is specified by the following beliefs:

1. There are the proportional of the standard deviations around the first lag coefficients to those for the coefficients of all other lags. This beliefs indicate that if the standard deviation around the first lag coefficients λ_1 to be small implied to strong beliefs random walks and are non-stationary of variables in the system.

2. The weight of each variable’s own lags λ_2 that explaining its variance is the same as the weights on other variables’ lags in an equation.

3. λ_3 indicated the proportionate of standard deviation of the coefficients in longer lags are smaller than the coefficients of earlier lags. Lag coefficients will be shrinked to zero over time and higher lags have smaller variance.

4. λ_4 indicated the proportionate of standard deviation of the intercept is based on the standard deviation of the residuals for the equation.

5. Sum of Autoregressive Coefficients Component (μ_5): This hyper-parameter implied 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 indicated to higher precision (smaller variance) about this belief. As $\mu_5 \to \infty$, the model interpret to the endogenous variables are described in terms of their first differences and there is no co-integration.

6. Correlation of coefficients / Initial Condition Component (μ_6) belief the level and variance of variables in the system should be proportionate to their means. If this

parameter is greater than zero, we belief that the precision of the coefficients in the model is proportionate to the sample correlation of the variables. As $\mu_6 \to \infty$, this mean that the prior have more weight on a model with a single common trend representation and intercepts close to zero. Table 1 will interpret hyper-parameters of Sims-Zha reference prior.

TABLE 1. Hyperparameters of Sims-Zha Reference Prior

Parameter	Range	Interpretation
λ_0	[0,1]	Overall scale of the error covariance matrix
λ_1	> 0	Standard deviation about A1 (persistence)
λ_2	=0	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

Source : Brandt, Patrick T. and John R. Freeman (2007)

3.2 Model forecasts

Brandt and Freeman (2007) evaluations of high dimensional BSVAR model specifications are hypothesis tests and are typically evaluated by probabilistic basis. For comparing the prior or structural specifications in a BSVAR model, we use the posterior probabilities that is the log marginal data density (also known as the log marginal likelihood) for the BSVAR model:

$$\log\big(m(Y)\big) = \log \Pr(Y|A_0, A_+) + \log \Pr(A_0, A_+) - \log \Pr(A_0, A_+|Y) \tag{18}$$

where $\log \Pr(Y \mid A_0, A_+)$ is the log likelihood for the BSVAR model, $\log \Pr(A_0, A_+)$ is the log prior probability of the parameters, and $\log \Pr(A_0, A_+ \mid Y)$ is the posterior probability of the BSVAR model parameters. Chib (1995) proposed a Gibbs sampler to the BSVAR model can compute the log marginal data density $\log\big(m(Y)\big)$. In matter of forecasting, the quality of a model is measured by its capacity to anticipate. We focus on statistical criteria to characterize the importance of forecasting error. Theil (1958) has been the first to perfect a very rigorous scientific evaluation criteria. One of criteria is the RMSE. This is defined as

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(Y_t^p - Y_t)^2} \qquad (19)$$

Where, Y_t is the actual value, Y_t^p is the predicted value at time t. T is the number of observations. On the measure point of view, we evaluate the forecasting model and examine the goodness of fit performance from RMSE.

4. Data

To find the long run relation of macroeconomic variable, we use a quarterly Thailand data set on the growth rate of GDP (gdp), inflation rate (inf), unemployment rate (un), growth rate of investment (inv: such that investment is gross capital changing plus gross capital fixed) and 3-month interest rate (r). Every variable was collected from 1997Q2 to2011Q2. Every variables were collected from Reuter Ecowin. Moreover, we checked the unit root of all variables by conducting an ADF-test which show that the results all had a variable that was neither a unit root or I(0). Then, we checked the order on lag of variables by the LR test statistic (each test at 5% level) and Hannan-Quinn information criterion. The result indicates that lag 2 is significant.

5. Results

There are two steps to specifying a BSVAR model. First, we identified the contemporaneous relationships among the variables in A_0. We separated them in two forms, one is a recursive form and the other is a non-recursive form. In the non-recursive form, we belief that the restrictions for the information in macroeconomic variables. The real economic variables GDP, unemployment, investment, and inflation variables contemporaneously affect the macroeconomic side. Brandt and Freeman (2007) interpret the structure of the contemporaneous relationships that we use to identify of the A_0 matrix is showed in Table 2. The columns of the A_0 matrix represent the equations and the rows are the innovations that contemporaneously enter each equation. The non-empty cells (marked with 1's) are contemporaneous structural relationships to be estimated while the empty cells are constrained to be zero. These empty cells in Table 2 show the absence of any contemporaneous impact of the row variables to column equation. Finally, Σ has $\left[5\times(5+1)\right]/2=15$ free parameters and the A_0 matrix in Table 2 has 15 free parameters in recursive form but 14 free parameter in non-recursive. Hence, it A_0 is over-identified for non-recursive.

TABLE 2. Recursive and Non-Recursive A_0

variable	Recursive					Non-Recursive				
	Equation					Equation				
	gdp	inf	un	inv	r	gdp	inf	un	inv	r
gdp	1					1	1	1		
inf	1	1				1	1			
un	1	1	1			1	1	1		
inv	1	1	1	1		1			1	1
r	1	1	1	1	1	1			1	1

The second is to choose values for the hyperparameters that reflect generally accepted beliefs about the dynamics of the economy. The beliefs are specified by the hyper-parameters. The priors are summarized in the Table 3. From table 3, our belief is that the macroeconomie variables are stationary or have a large standard deviation around the first lag coefficient ($\lambda_1$to be large) in terms of growth rate or percentage. Because of the based on log marginal density, RMSE shows that model 1 to model 4 is greater than the log marginal density and less RMSE of model 5 to model 8 (model 5 to model 8 have $\lambda_1$that is small than the mean non-stationary or small standard deviation).

In comparision, there is more or less weight on the sum of autoregressive coefficients component (μ_5). We found that more weight models are better than less weight model based on both log marginal density and RMSE. Moreover, non-recursive, model 3 is the best posterior fit measures for forecasting (RMSE is least) . For model 1 to model 8 in table 3, we computed the impulse responses. Based on the $\log\left(m\left(Y\right)\right)$, the prior of model 3 that is to our belief produces the most dynamically meaningful in macroeconomie theory. The impulse responses for model 5 to 8 (non-stationary) have error bands that vary widely and impossible for an interpretation of the magnitudes and direction of the dynamics.

The results of impulse response for model stationary or large standard deviation for parameters with more weight on the sum of autoregressive coefficients can interprete the meaningful of dynamic in macroeconomic variable which has a much lesser weight. The responses to shocks in model 1 (less weight) is more permanent and dissipate more slowly than model 3. Model 3 have more correlation among the coefficients for variable in equation and more rapid lag decay (and thus faster equilibration to shocks than with the model 1).

Figure 1 presents the responses of the economic equations to shocks in the macroeconomic variables. Each row are the responses of equation for a shock in the column variable. Responses are median estimates with 68% confidence region error bands, computed pointwise over a 12 quarter time horizon.

TABLE 3. Eight BSVAR prior and their posterior fit measures

Hyperparameters	Model 1 Non-Recursive	Model 2 Recursive	Model 3 Non-Recursive	Model 4 Recursive
lambda0	0.9	0.9	0.9	0.9
lambda1	5	5	5	5
lambda3	1	1	1	1
lambda4	0.1	0.1	0.1	0.1
lambda5	0.07	0.07	0.07	0.07
mu5	0	0	5	5
mu6	5	5	5	5
Log Pr(A+|Y, A0)	283.0062	283.0062	298.9691	298.9691
Log marginal density, Pr(Y)	-746.8386	-710.8336	-705.9789	-757.5952
RMSE	17.5199	22.18763	11.39292	31.86254

TABLE 3 (cont.) Eight BSVAR prior and their posterior fit measures

Hyperparameters	Model 5 Non-Recursive	Model 6 Recursive	Model 7 Non-Recursive	Model 8 Recursive
lambda0	0.9	0.9	0.9	0.9
lambda1	0.1	0.1	0.1	0.1
lambda3	1	1	1	1
lambda4	0.1	0.1	0.1	0.1
lambda5	0.07	0.07	0.07	0.07
mu5	0	0	5	5
mu6	5	5	5	5
Log Pr(A+|Y, A0)	369.5155	369.5155	377.2721	377.2721
Log marginal density, Pr(Y)	-896.1246	-905.0454	-899.5005	-909.5677
RMSE	38.91123	35.50938	50.60091	39.96849

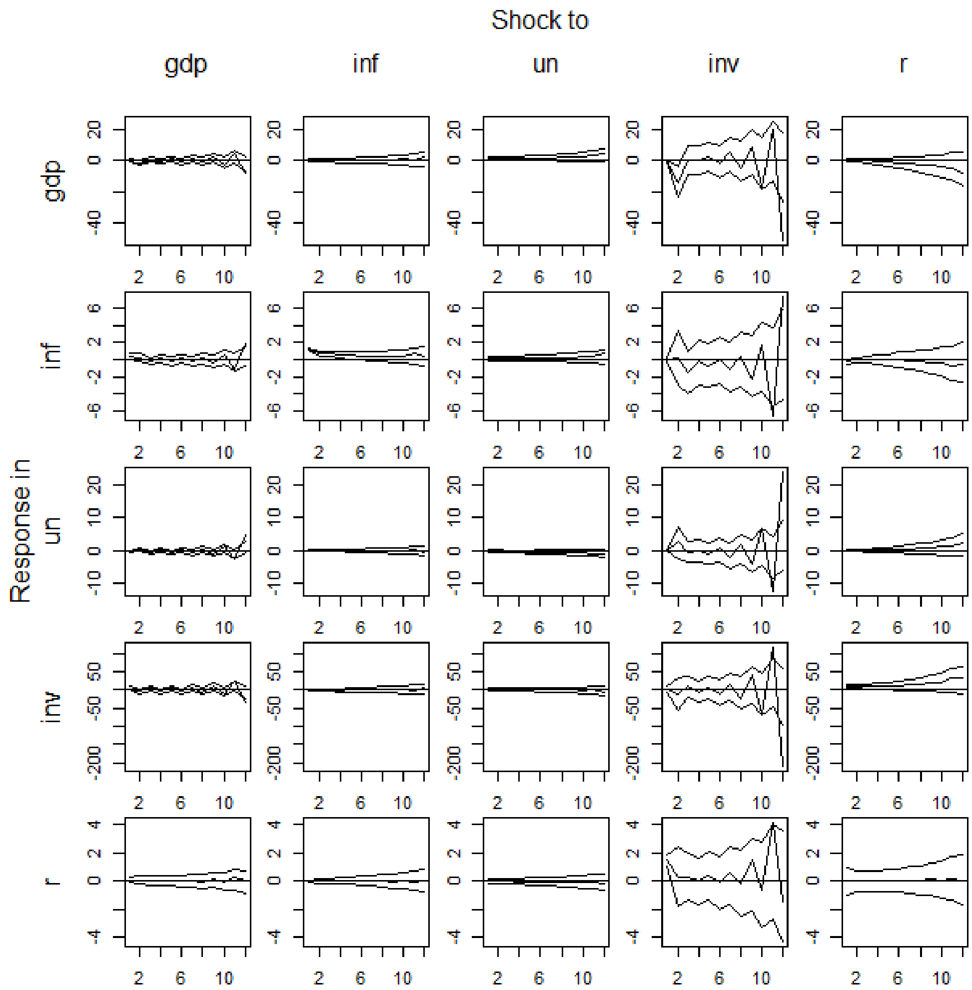

Figure 1. Impulse Responses of Macroeconomic Variables to Shocks Over 12 Quarters. Responses are median responses computed from the BSVAR posterior. Error bands are 68% or approximately one standard deviation around the median response.

The interpretation of the impulse responses 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 BSVAR models (Waggoner and Zha 2003). Because of no unique correspondence of shocks to equations in a simultaneous system like an SVAR. Thus positive shocks to one equation may imply negative shocks to other equations (Brandt and Freeman (2007)).

In figure 1, The responses of the economy to shocks in the macroeconomic variables indicate that changes in exogenous variables or government policy act as the predictable and sizeable effects on the economy. Over 12 quarters, when shock occurs to the GDP, all variables swing around to the zero rate which converse to an equilibrium in long run.

The shock in inflation rate and unemployment rate effect the same patten of response in all variables. The magnitude response in growth rate GDP, unemployment rate and interest rate are near zero. But positively response in inflation rate equation and move to a converse after 4 quarters. This is an indication that the exogenous shock (such as fiscal policy and monetary policy) to inflation rate and unemployment rate are not affected too much with the endogenous macroeconomic variables, and there is a converse to equilibrium in the long run.

Interest rate shock or using monetary policy has more effect to the macroeconomic variables than other variables. The impulse response show the negative response for growth rate of GDP and inflation rate that is consistent with the macroeconomic theory. In addition, positively response in unemployment rate means that positive interest rate shock would reduce the aggregate demand thus implying that the producer would hire less workers. Moreover, a response in interest rate is near zero thus implying it had adjustment over time when a shock occurs. However, the response in investment rate has a positive direction to the interest rate shock.

The most shock effect to the system is the investment rate shock which is shown in table 3. All macroeconomic variables have large variance over time. Therefore, this shock provides a divergement towards the long run. This implementation suggests that fiscal and monetary policy should be carefully used for stimulating the economic from other exogenous shock. If the government divides a large share of balance budget deficit to investment, then the government has to make some restriction or condition to use this share for guaranteeing that there will be a less variance of movement in the business cycle. Should this not be the case then the large size variance of the business cycle becomes a serious problem to the government.

6. Concluding remarks

Bayesian VARs are able to handle large unrestricted VARs. Thus, we can analyse structure VARs that contain many variables of macroeconomic. Belief into the contemporaneous relationships appears in matrix A_0. In addition, the benefit of the structural VAR approach allows us to estimate whether the contemporaneous coefficient should be unrestricted. Using a Bayesian approach also allows us to summarize our uncertainty about such contemporaneous restrictions. This paper used quarterly data set on the growth rate of GDP (gdp), inflation rate (inf), unemployment rate (un), growth rate of investment (inv) and 3-month interest rate (r) which were collected from 1997Q2 to2011Q2. ADF-test shows the result integrated ordor zero I(0) of all variables. After that, using the LR- test statistic lead to an indication that the lag length of variable in systems had lag 2 that is significant.

We consider the vary set of hyper-parameters. The result shows that based on $\log(m(Y))$ and RMSE criterion, model 3 is the best fitted model which to our belief data set has a stationary or large standard deviation around the first lag coefficient and more weight on the sum of autoregressive coefficients component ; which is appropriate for forecasting and calculating the impulse response.

In the analytical of impulse response, we found that the shock to growth rate of GDP, inflation rate, unemployment rate and interest rate, make a response in all variables that move in a converse to an equilibrium in the long run. Only the shock effect to investment rate is the major shock problem for this system. The government should take caution when using any policies towards investment and applying some restriction for controlling a large variance movement in the business cycle. Further study should be added the policy variables such as fiscal policy, monetary policy and trade policy. Moreover, nonlinear VARs model should be compared to BSVAR. Because of time series variables have fluctuated behavior.

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