CHAPTER 3

Data and Methodology

3.1 Data

The main purpose of this study is to dating the effect of volatility as well as identifies Quantitative easing factors that lead a Thailand, Indonesia and Philippines markets (exchange rate market, stock market and bond market) from one regime to another regime and also signal ahead a turbulent regime as an early warning systems.

To understand an impact of U.S. Quantitative Easing to Thailand ,Indonesia and Philippines currencies ,stock and bond market, the raw monthly data, purchasing U.S.'s Mortgage back securities (MBS), purchasing U.S.'s Treasury securities (TS), Fed's balance sheet (FB), Stock exchange of Thailand index (SET), Jakarta Composite Index (JKSE), Philippine Stock Exchange composite index (PSEi), THB/USD (Exth), IDR/USE (Exind), PHP/USD (Exphp), Thai government bond yield (THY), Indonesia government bond yield (INDY) and Philippines government bond yield (PHY) are collected from Thomson Reuters DataStream, from Financial Investment Center (FIC), Faculty of economics, Chiang Mai University and www.federalreserve.gov, for the period 14 January 2009 to 10 July 2014. Whereas, all of these observation have been transform to the first difference of logarithm form in order to make them stationary because the stationary time series could avoid the spurious regression problem which obtain when using non-stationary time series (Gujarati, 2003).

The first difference of logarithms form of variable i at time t are calculated as follows:

$$RY_{i,t} = (\ln(Y_{i,t}) - \ln(Y_{i,t-1})) \tag{3.1}$$

where $RY_{i,t}$ is the expected return on variable i at time t, $Y_{i,t}$ and $Y_{i,t-1}$ are the closing prices or index of the variable i for weeks t and $t-1$, respectively, and $\ln$ is natural logarithm.

Thus, the expected return of each variable are denote as follows:

RMBS	=	the rate of return on Mortgage back securities.
RTS	=	the rate of return on US's Treasury securities.
RFB	=	the rate of return on Fed's balance sheet.
RSET	=	the rate of return on Stock exchange of Thailand index.
REXth	=	the rate of return on Thai baht against US dollar.
*REX*ind	=	the rate of return on Indonesia rupee against US dollar.
REXph	=	the rate of return on Philippines peso against US dollar.
RJKSE	=	the rate of return on Jakarta Composite Index.
RPSEi	=	the rate of return on Philippine Stock Exchange composite index.
RTHY	=	the rate of return on Thai government bond yield.
RINDY	=	the rate of return on Indonesia government bond yield.
RPHY	=	the rate of return on Philippines government bond yield.

3.2 Model of Study

The MS-BVAR model is estimated using block EM algorithm where the blocks are Bayesian Vector Autoregressive (BVAR) regression coefficients for each regime (separating for intercepts, AR coefficient, and error covariance) and transition matrix.

Sim, Waggoner, and Zha (2008) provided tools to estimate and conduct inference on MS-BVAR models of lag length p as follow:

$$\begin{bmatrix} RMBS_t \\ RTS_t \\ RFB_t \\ RSET_t \\ REXth_t \\ REXind_t \\ REXph_t \\ RJKSE_t \\ RPSEi_t \\ RTHY_t \\ RINDY_t \\ RPHY_t \end{bmatrix} \begin{bmatrix} A_0^{RMBS_t}(S_t) \\ A_0^{RTS_t}(S_t) \\ A_0^{RFB_t}(S_t) \\ A_0^{RSET_t}(S_t) \\ A_0^{REXth_t}(S_t) \\ A_0^{REXind_t}(S_t) \\ A_0^{REXph_t}(S_t) \\ A_0^{RJKSE_t}(S_t) \\ A_0^{RPSEi_t}(S_t) \\ A_0^{RTHY_t}(S_t) \\ A_0^{RINDY_t}(S_t) \\ A_0^{RPHY_t}(S_t) \end{bmatrix} = \begin{bmatrix} RMBS_{t-1} & A_1(S_t) & \cdots & RMBS_{t-p} & A_p^{RMBS_t}(S_t) \\ RTS_{t-1} & A_1(S_t) & \cdots & RTS_{t-p} & A_p^{RTS_t}(S_t) \\ RFB_{t-1} & A_1(S_t) & \cdots & RFB_{t-p} & A_p^{RFB_t}(S_t) \\ RSET_{t-1} & A_1(S_t) & \cdots & RSET_{t-p} & A_p^{RSET_t}(S_t) \\ REXth_{t-1} & A_1(S_t) & \cdots & REXth_{t-p} & A_p^{REXth_t}(S_t) \\ REXind_{t-1} & A_1(S_t) & \cdots & REXind_{t-p} & A_p^{REXind_t}(S_t) \\ REXph_{t-1} & A_1(S_t) & + \cdots + & REXph_{t-p} & A_p^{EXph_t}(S_t) \\ RJKSE_{t-1} & A_1(S_t) & \cdots & RJKSE_{t-p} & A_p^{RJKSE_t}(S_t) \\ RPSEi_{t-1} & A_1(S_t) & \cdots & RPSEi_{t-p} & A_p^{RPSEi_t}(S_t) \\ RTHY_{t-1} & A_1(S_t) & \cdots & RTHY_{t-p} & A_p^{RTHY_t}(S_t) \\ RINDY_{t-1} & A_1(S_t) & \cdots & RINDY_{t-p} & A_p^{RINDY_t}(S_t) \\ RPHY_{t-1} & A_1(S_t) & \cdots & RPHY_{t-p} & A_p^{RPHY_t}(S_t) \end{bmatrix} + \begin{bmatrix} C^{MBS_t}(S_t) \\ C^{RTS_t}(S_t) \\ C^{RFB_t}(S_t) \\ C^{RSET_t}(S_t) \\ C^{REXth_t}(S_t) \\ C^{REXind_t}(S_t) \\ C^{REXph_t}(S_t) \\ C^{RJKSE_t}(S_t) \\ C^{RPSEi_t}(S_t) \\ C^{RTHY_t}(S_t) \\ C^{RINDY_t}(S_t) \\ C^{RPHY_t}(S_t) \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{RMBS_t} \\ \varepsilon_t^{RTS_t} \\ \varepsilon_t^{RFB_t} \\ \varepsilon_t^{RSET_t} \\ \varepsilon_t^{REXth_t} \\ \varepsilon_t^{REXind_t} \\ \varepsilon_t^{REXph_t} \\ \varepsilon_t^{RJKSE_t} \\ \varepsilon_t^{RPSEi_t} \\ \varepsilon_t^{RTHY_t} \\ \varepsilon_t^{RINDY_t} \\ \varepsilon_t^{RPHY_t} \end{bmatrix} \square \begin{bmatrix} \Gamma_{RMBS_t}^{-1}(S_t) \\ \Gamma_{RTS_t}^{-1}(S_t) \\ \Gamma_{RFB_t}^{-1}(S_t) \\ \Gamma_{RSET_t}^{-1}(S_t) \\ \Gamma_{RExth_t}^{-1}(S_t) \\ \Gamma_{RExind_t}^{-1}(S_t) \\ \Gamma_{RExph_t}^{-1}(S_t) \\ \Gamma_{RJKSE_t}^{-1}(S_t) \\ \Gamma_{RPSEi_t}^{-1}(S_t) \\ \Gamma_{RTHY_t}^{-1}(S_t) \\ \Gamma_{RINDY_t}^{-1}(S_t) \\ \Gamma_{RPHY_t}^{-1}(S_t) \end{bmatrix} \quad (3.2)$$

whereas

$Y_t^{'}$ = n –dimensional column vector of endogenous variables at time t including RMBS, RTS, RFB, RSET, RJKSE, PSEi, REXth, REXind, REXph, RTHY, RINDY and RPHY

A_0 = n×n non singular matrix

s_t = h dimension vector of regimes (unobserved variable)

h = the finite set of integers H

A_j = n×n matrix coefficient

C = vector of intercept terms

ε_t = the vector of n unobserved shocks

Γ = n×n diagonal matrix of the elements of ε_t

p = the number of lag

3.3 Methodology

Before estimating the parameter, the researcher separates the parameter into 3 groups as follows

1) TIP stock markets consisting of RFB, RTS, RMBS, RSET, RJKSE and RPHEi.

2) TIP exchange markets consisting of RFB, RTS, RMBS, RExth, RExind, and RExph.

3) TIP bond markets consisting of RFB, RTS, RMBS, RTHY, RINDY, and RPHY

I use the following techniques to estimate each groups using MS-BVAR method as follows:

1. Stationary of the data is tested by using the Augmented Dickey-Fuller (ADF) test, which is given as follows:

RY_t is a random walk:

$$\Delta RY_t = \alpha RY_{t-1} + \sum_{i=2}^{p} \gamma_i \Delta RY_{t-i} + u_t \qquad (3.3)$$

RY_t is a random walk with drift:

$$\Delta RY_t = \beta_0 + \alpha RY_{t-1} + \sum_{i=2}^{p} \gamma_i \Delta RY_{t-i} + u_t \qquad (3.4)$$

RY_t is a random walk with drift and trend:

$$\Delta RY_t = \beta_0 + \beta_1 t + \alpha RY_{t-1} + \sum_{i=2}^{p} \gamma_i \Delta RY_{t-i} + u_t \qquad (3.5)$$

whereas

RY_t = the endogenous variable including RMBS, RTS,RFB, RSET, RJKSE,RPSEi,R EXth ,R EXind ,REXph, RTHY, RINDY and RPHY

β_0 = the constant term

β_1 = the coefficient time trend (t)

α = the coefficient of lagged value (Y_{t-1})

u_t = error term

By lagged term (p), I add a number of lag terms until the data have no autocorrelation. Then, I test all these equations using Ordinary Least Square (OLS) in order to the estimated a value of α and standard error. Compare the resulting of t-statistic value with critical t-statistic value in the ADF tables. If the value of t-statistic exceeds the ADF t-statistic value, we can reject the null hypothesis, in which case the time series is stationary. On the other hand, if the value of t-statistic does not exceeds the ADF t-statistic value we do not reject the null hypothesis, in which case the time series is non-stationary whereas, the null hypothesis and alternative hypothesis presents as follows

$$H_0 : \alpha = 0 \text{ (} RY_t \text{ is non-stationary)}$$

$$H_0 : \alpha \neq 0 \text{ (} RY_t \text{ is stationary)}$$

2. Estimating MS-BVAR(p) of Nason and Tallman (2013) which provided by Sim, Waggoner, and Zha (2008) to estimate and conduct inference on MS-BVAR models of lag length k using multi-step procedure as follows:

2.1 Setting the random walk, smoothness, duration prior on the MS-BVAR(p)

Sims and Zha (1998) suggested the prior parameters that we believe are about the conditional mean of the coefficients of the lagged effects, as specified by the following beliefs:

1) There are proportional standard deviations around the first lag coefficients for those of the coefficients of all the other lags. This belief indicates that if the standard deviation around the first lag coefficients λ_1 is to be small, then that would imply a strong belief of random walks and the variables are non-stationary

2) The weight of each variable's own lags λ_2, which explains its variance is the same as the weights of the other variables' lags in an equation.

3) λ_3 indicates that the proportionate of standard deviation of the coefficients in the longer lags are smaller than the coefficients of the earlier lags. Lag coefficients will shrink to zero over time; also, higher lags have smaller variance.

4) λ_4 indicates that the proportionate of the 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 implies the accuracy of the belief that the average lagged value of a variable *i* predicts a better variable *i* than the averaged lagged values of a variable $i \neq j$. Larger values of μ_5 indicate higher accuracy (smaller variance) of this belief. As $\mu_5 \to \infty$, the model interprets that the endogenous variables are described in terms of their first differences and that there is no co-integration.

6) Correlation of coefficients/Initial Condition Component (μ_6) supposes the level and variance of variables in the system should be proportionate to their means. If this parameter is greater than zero, then we believe that the accuracy of the coefficients in the model is proportionate to the sample correlation of the variables. As $\mu_6 \to \infty$, this means that the prior has more weight on the model with a single common trend representation and that the intercepts close to zero.

In this study, I proposes Normal-wishart prior, Normal-flat prior and Flat-flat prior as prior in MS-BVAR(p) model. These priors have a different distribution which is inferred as an economic condition, including normal economy, volatile economy, and high volatile economy. Therefore, the result of posterior estimation via Gibbs sampler will be sensitive to these priors and the value of hyper-parameter that we believe. These priors are used for the independent Dirichlet process for MS process. Table 3.1 will interpret the value of hyper-parameters for each prior as follows:

Table 3.1 Hyper-parameters of Sims–Zha Reference Prior

Prior	Range		
Hyper-Parameter	Normal-wishart	normal-flat	flat-flat
λ_0	0.6	0.8	1
λ_1	0.1	0.15	1
λ_3	2	1	1
λ_4	0.25	0.25	1
λ_5	0	1	0
u_1	0	0	0
u_2	0	0	0

Adapted from, Brandt, Patrick T (2013)

2.2 Given estimates of $\Theta_j(A_0, A_1, ...A_h; \Gamma(1), ...\Gamma(h), C)$, $j = 1,...,h$ of the MS-BVAR(p), employing the Markov chain Monte Carlo(MCMC) integration method of Gibbs sampler in obtaining the marginal likelihoods and bayes factor or marginal posterior distribution on interest for inference by running 1,000 steps of MCMC simulator

The following describes the Gibbs sampler procedure:

Given $\tilde{A} = A_0, A_1, ..., A_h$ and $\tilde{\Gamma} = \Gamma_0, \Gamma_1, ..., \Gamma_h$. Then, let $\tilde{A}_0$ and $\tilde{\Gamma}_0$ be two arbitrary starting values of $\tilde{A}$ and $\tilde{\Gamma}$ .The Gibbs sampler proceeds as follows:

1) Draw $\tilde{A}_1$ from $f_1(A_1 | A_{2,0}, A_{3,0}, Y_t, M_i)$.

2) Draw $\tilde{\Gamma}_1$ from $f_2(\Gamma_2 | \Gamma_{3,0}, \Gamma_{1,1}, Y_t, M_i)$.

3) Draw C_1 from $f_3(C_3 | C_{1,1}, C_{2,1}, Y_t, M_i)$.

This completes a Gibb iteration and these parameters become $\tilde{A}_1, \tilde{\Gamma}_1$ and C_1.

Next, using the new parameters as starting values and repeating the prior iteration of $\tilde{A}_0$, $\tilde{\Gamma}_0$ and C draws, complete another Gibbs iteration to obtain the updated parameters $\theta_{1,2}$, $\theta_{2,2}$ and $\theta_{3,2}$. Repeating the previous iterations for 1,000 times to obtain a sequence of random draws:

$(\tilde{A}_1, \tilde{\Gamma}_1, C_1), ..., (\tilde{A}_{1,000}, \tilde{\Gamma}_{1,000}, C_{1,000})$

2.3 Constructing the posterior of an MS-BVAR(p) (M_i) by drawing 5,000 times from the Starting form $(\tilde{A}_1, \tilde{\Gamma}_1, C_1), ..., (\tilde{A}_{1,000}, \tilde{\Gamma}_{1,000}, C_{1,000})$ for Gibbs sampling the posterior is as follows: (Braunt, 2009)

Process 1: Filter/smooth/sample Run the forward filter to get estimates of $\Pr(S_t^i | Y_{t-1})$ from $t = 1, 2, ...T$ Then backwards sample $\Pr(S_t^i | Y_t, S_T^i)$ from $t = T, T-1, T-2, ...,1$ using multi-move steps to get posterior sample of the states.

Process 2: Sample MS process Draw Q^i from the Dirichlet distribution with prior for the state-space transitions Q^i in the marginal conditional distributions for posterior distribution.

Process 3: Sample h regressions Subject to step 1, classify the observations for Y_t and Y_{t-p} and run the multivariate regressions to estimate $\tilde{\Theta}_j^i$ for $j = 1, ..., h$. Repeating step 1-3, 5,000 times.

2.4 Choosing among the competing MS-BVAR(p) models by calculating posterior odds ratio using log marginal data densities computed on the posterior distributions of the previous step

2.5 Determine the lag length of the MS-BVAR model because the inference in the MS-BVAR model also depends on the correct lag length specification. If the model has not correct lag length, it will face with the mean square forecast errors VAR and also generates autocorrelated errors

2.6 Chib (1997) purposed estimation and comparison of multiple change point models. He provided 3 models of change point case as follows:

M_1 is the model with no change point.

M_2 is the model with one change point.

M_3 is the model with two change point.

Therefore, this model also examines the number of change point as well. Let sum up the above information, including prior, lag length and number of change point, we have to estimate.In comparing these 21 models, the model with the highest value of log marginal likelihood preferred.

Table 3.2 Competing MS-BVAR Model

Prior	MS-BVAR model	No-change point	One change point	Two change point
Normal-wishart	Lag 1	Model1		
Normal-flat	Lag 2	Model2	Model3	Model4
Flat-flat	Lag 3	Model5	Model6	Model7
Normal-wishart	Lag 1	Model8	Model9	Model10
Normal-flat	Lag 2	Model11		
Flat-flat	Lag 3	Model12	Model13	Model14
Normal-wishart	Lag 1	Model15	Model16	Model17
Normal-flat	Lag 2	Model18	Model19	Model20
Flat-flat	Lag 3	Model21		

4. Rerunning the MS-BVAR(p) models which achieves the best fit to the data with the highest value of log marginal likelihood to produce the transition probabilities $Q_1,...,Q_h$

5. The estimated MS-BVAR(p) model produce probabilities of regime $j, j=1,....,h$ at date t.

6. Constructing an Impulse response and error band s are all based on a Monte Carlo sample of 10,000 draws. For all the moving average responses, the same procedure is used to draw the sample of impulse responses. A sample is taken from the

posterior of BVAR models coefficients. Then, the draw is used to compute the error bands for that draws. (Brandt and Freeman,2005)

7. Forecasting is an under emphasized goal of many researchers because it is the most important and powerful tools of inference and policy analysis. To forecast the MS-BVAR model, there were the basic algorithm given by both Krolzig (1997) and Fruhwirth-Schnatter (2006) as follow:

1) Simulating the regime conditional on S_t sample the hidden Markov path recursively for S_{t+h} for $h = 1, ..., s$. These are based on a MS-BVAR(p) forecast of the Markov transition probabilities for $\Pr(S_{T+h} | s_{T+h-1})$

2) Simulating the forecasts conditional on the regimes drawn in the previous steps, use the parameters from the i^{th} draw of the posterior to construct a reduced form MS-BVAR(p) forecast for period T+h. Formally, consider an h-step forecast equation for the reduced form MS-BVAR(p) model

Iterating the algorithm returns a posterior sample of the forecasts where the forecasts account for the regime prediction uncertainty in the MS process. Generate the distribution of the conditional forecasts from MS-BVAR(p) using Gibbs sampler. Then, use this conditional forecast to augment the data and resample the parameters.