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Relationships Among Prices of Rubber in ASEAN: Bayesian Structural VAR Model

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Abstract : International rubber markets are seen to be volatile due to the high competitiveness between major rubber export markets. This paper analyses the causal impact price transmission among ASEAN over the period of 2008 to 2015. The Bayesian structural VAR model is conducted to analyse relationship among rubber export price for top four rubber producing in ASEAN. We considered the varying sets of hyper-parameters to obtain the best fit model. The results reveal that Indonesia and Thailand have more efficiency when it comes to adjustment of their rubber prices than Malaysia and Vietnam.

Keywords : Bayesian estimation; structural vector autoregression; time varying with stochastic volatility; ASEAN Rubber.
2010 Mathematics Subject Classification : 47H09; 47H10.

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1 Introduction

One of the key products of Southeast Asias agricultural sector is rubber. It is used extensively in many applications and products, either just as itself or in combination with other materials. In most of its useful forms it has a large stretch ratio and high resilience, and is extremely waterproof. This product is important and strategic for Southeast Asia; hence it has been included among the top eleven priority products of the ASEAN Economic Community (AEC) for 2015. The

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product rubber is expected to be the engine of growth for Southeast Asias economy and the powerhouse that will transform the ASEAN economic integration paths from being channels of free flow of goods into channels of free flow of capital. The latter has been identified so because of its ability to enhance trade and investment integration among the ASEAN members.

Rubber export has been growing steadily in the last decade. Thailand, Malaysia, Indonesia, and Vietnam have become the major countries that produce and export rubber in the ASEAN region. In 2012, these countries were ranked as the worlds largest rubber producers as well as the worlds largest exporters. These three exporting nations provide about 82% of the amount of rubber exported to all the different parts of the world. The major markets for Thailands rubber are China, Japan, and the USA, to which 32.5% of the total amount of rubber was exported. The major markets for Malaysias rubber are located in China, Germany, South Korea, and the USA, where the export figure stands at 12.34%. The major markets for Indonesias rubber are the USA, Japan, China, and South Korea, where the export figure stands at 33.73%. The major markets for Vietnams rubber are China, Malaysia, and India, where the export figure is 3.8%. The leading buyers of rubber are China, the USA, and Japan.

Under globalization, the economy changes rapidly in the agricultural market. There has been dense interaction between the countries in terms of interdependence and competition, so any change in trade policies between the different countries is bound to have an effect on all the countries involved. Just as a positive or a negative shock will have an effect on the export price of rubber in that country, the same would also have an effect on the price of rubber of other countries. Consequently, this paper aims to study the relationships among export prices of rubber in ASEAN.

This paper investigates the structural VAR of the relationships among export prices of rubber in the ASEAN region, as well as conducts an analysis on the impulse response for finding an explanation for the movement of the export price of the rubber variable when it comes as a shock to the system. Moreover, we used the Bayesian structural VAR model because it assists us in using a few data sets in the VAR models which face the degree of freedom problem. We compared the varying sets of hyper-parameters, which is true to our prior belief in the Bayesian structure VAR model. In addition, we also allowed the parameters to vary over time in order to capture the variety effect of rubber export price among Thailand, Malaysia, Indonesia, and Vietnam and to study the dynamic relationship between these variables.

The model estimation is separated into two parts. First, we contemplated which set of hyper-parameters would be appropriate by basing the decision on the log marginal data density. After that, a comparison was made with the restriction and the non- restriction in the coefficients for contemporaneity. This was followed up with an estimation and analysis to gauge the impulse response in the system.

The paper is organized as follows: Section 2, we review the previous rubber study and methodology. Section 3, we describe methodologies conducted in this paper. Section 4, we perform the structural analysis on the rubber export price in

ASEAN. Conclusion is provided in Section 5.

2 Literature Review

Among various studies on export price of rubber in ASEAN, Pastpipatkul [1] used Johansen Juselius method to analyze the relationship between the existing price of rib smoked sheet (RSS) and the previous RSS price in the Hat Yai market. The results of this study described a relationship between the current price and the previous price. Rakkarndee [2] found how RSS export price is dependent on the world market. Laksana [1] found that the prices of Indonesian export rubber (which are exported to Japan) have a significant influence on Thailands rubber exportation. Rosmerya [3] analyzed the competitiveness of Indonesian natural rubber in the global market: the markets in the USA, Japan, and China were applied with the Revealed Comparative Advantage (RCA), Export Specialization Index (ESI), and Competitiveness Matrix. The results of this research showed that the competitiveness of the Indonesian natural rubber commodity is stronger than the world average: the Indonesian natural rubber commodity is much more highly competitive than the average natural rubber exports from other countries to the markets in the United States, Japan, and China. Thus, from the information provided, it is evident that there has been just a meager amount of study with regard to the relationships among export prices of rubber in ASEAN. Therefore, this paper will attempt to make an analysis on the rubbers export price movement in each country within the ASEAN region.

Vector autoregressions (VAR) have mostly been the traditional tools used for structural analysis and forecasting. However, the model do not impose restrictions on the parameters and provide a general concept to capture complex data relationships. This carries the risk of over-parameterization due to the typical sample size available for the variables. The number of unrestricted parameters that can be estimated becomes rather limited. Because of this, VAR applications are usually based on a small number of variables. The sizes of the VAR used in the empirical applications range from about three to ten variables. This creates an omitted variable bias. This fact has led to unwanted consequences for both structural analysis and forecasting for not being highly accurate. In addition, the size limitation is a problem for applications that have larger sets of variables. From the VAR literature, the solution is to analyze whether the data sets are large or less so that they can be used to define a core set of variables and for adding one variable. With this approach, it is difficult for the comparison of the impulse responses between the models to be able to do justice. To solve these problems, recent literature on this has proposed methods to impose restrictions on the covariance structure, such as limiting the number of parameters for estimation. In this paper, we show that by applying the Bayesian structural VAR (BSVAR) shrinkage, we are able to handle large unrestricted amount of VAR. Thus, a VAR framework can be applied to empirical studies that can analyze many variables of time series type. Thus, we can analyze the structural VAR models that contain the many variables of the export price of rubber in ASEAN. For this reason, the Bayesian structural VAR is a valid alternative for analyzing large dynamic systems. We used the proposals put forward by Doan,Litterman, and Sims [4] and Litterman [5]. Litterman [5] found that applying the Bayesian shrinkage in the VAR that contains six variables can forecast the performance much better. This suggests that over-parametrization can become the appropriate system for a model size, and that shrinkage is a potential solution to this problem. However, although Littermans priors is a traditional standard tool in applied time series data ([6, 7]), the imposition of priors has not been considered sufficient to deal with the larger models.

3 Methodology

3.1 Bayesian VAR Models

3.1.1 Sims VAR Method

Sims [6] suggested that VAR model is 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 [8]. The VAR(p) model can be written as

$$y_t = a_0 + \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t \tag{3.1}$$

Let y_t be the matrix $MT \times 1$ which is the vector of those variables which have T observations for each dependent variable. The classical VAR model explains each variable by its own lag p and the other variables by the lag p of all. A_j is $M \times M$ matrix of coefficients, a_0 is the deterministic component that includes a constant and seasonal dummies, while ε_t stands for the white noise processes of a zero-mean vector with positive definite contemporaneous covariance matrix Σ_ε and zero covariance matrices at all the other lags. In the general form, Y is defined as the $T \times M$ matrix which has T observations for each dependent variable in the 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

$$X = \begin{bmatrix} x_1 \\ \vdots \\ x_T \end{bmatrix} \tag{3.2}$$

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

$$Y = XA + E \tag{3.3}$$

or

$$y = (I_M \otimes X)\alpha + \varepsilon \tag{3.4}$$

where $\varepsilon \sim N(0, \Sigma \otimes I_T)$. The likelihood function can be calculated from the sampling density, $p(y|\alpha, \sum)$. It can be separated into two parts when it is a function of the parameters, one a distribution for α given Σ and the other where Σ^{-1} has a Wishart distribution. That is,

$$\alpha|\Sigma, y \sim N\left(\hat{\alpha}, \Sigma \otimes (X'X)^{-1}\right) \tag{3.5}$$

and

$$\Sigma^{-1}|y \sim W\left(S^{-1}, T-K-M-1\right) \tag{3.6}$$

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

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

3.1.2 Normal-Wishart Prior

Koop and Korobilis [9] stated that the natural conjugate prior assumes each equation to have the same explanatory variables and restriction of prior covariance of the coefficients in any two equations that are proportional to one another. So, posterior simulation algorithms, such as the Gibbs sampler, are required for the Bayesian inference in the models. The Normal of$\alpha|\Sigma$ and Σ^{-1} being Wishart was in the natural conjugate prior. Moreover,α and Σ are not independent if we set the prior for α to depend on Σ. For this part, we used the independent-of-one-another prior in the VAR coefficients and the error covariance, which is called as independent Normal-Wishart prior.

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

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

where $t = 1, ..., T$ are the observations for $m = 1, ..., M$ variables. And, y_{mt} is the t^{th}observation for the m^{th} variable, z_{mt} is a k_m vector containing the t^{th} observation of the vector of explanatory variables relevant to 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, if we allow z_{mt} to vary across equations, then it means that we allow for the possibility of a restricted VAR. In other words, it restricts some of the coefficients of the lagged dependent variables to be zero.

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

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

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

where β is a $k \times 1$ vector, 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

$$y = Z\beta + \varepsilon \tag{3.7}$$

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

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

where

$$\beta \sim N\left(\underline{\beta}, \underline{V}_\beta\right) \tag{3.8}$$

and

$$\Sigma^{-1} \sim W\left(\underline{S}^{-1}, \underline{v}\right). \tag{3.9}$$

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

If we use this prior, the equation for the calculation of the joint posterior $p\left(\beta, \Sigma^{-1}|y\right)$ will not be in a convenient form. So, we allow for an easy Bayesian analysis. However, the conditional posterior distributions $p\left(\beta|\Sigma^{-1}, y\right)$ and $p\left(\Sigma^{-1}|y, \beta\right)$ have convenient forms.

$$\beta|y, \Sigma^{-1} \sim N\left(\bar{\beta}, \bar{V}_\beta\right), \tag{3.10}$$

where

$$\bar{V}_\beta = \left(\underline{V}_\beta^{-1} + \sum_{t=1}^{T} Z'_t \Sigma^{-1} Z_t \right)^{-1} \tag{3.11}$$

and

$$\bar{\beta} = \bar{V}_\beta \left(\underline{V}_\beta^{-1} \underline{\beta} + \sum_{t=1}^{T} Z'_t \Sigma^{-1} y_t \right) \tag{3.12}$$

Furthermore,

$$\Sigma^{-1} | y, \beta \sim W \left(\bar{S}^{-1}, \bar{v} \right), \tag{3.13}$$

where $\bar{v} = T + \underline{v}$ and $\bar{S} = \underline{S} + \sum\limits_{t=1}^{T} (y_t - Z_t\beta)(y_t - Z_t\beta)'$.

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

3.1.3 BSVAR Model

Sims and Zha [7], Waggoner and Zha [10], and Brandt and Freeman [11] suggested the use of the estimated Bayesian structural VAR (BSVAR) model. The BSVAR model is based on a dynamic simultaneous equation model. The prior is to be set for the structural parameters. Waggoner and Zha [12] suggested the basic SVAR model as

$$y'_t A_0 = \sum_{l=1}^{p} Y'_{t-l} A_l + z'_t D + \varepsilon'_t \ , t = 1, ..., T \tag{3.14}$$

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

$$\begin{aligned} E\left[\varepsilon_t | y_1, ..., y_{t-1}, z_1, ..., z_{t-1}\right] = 0 \\ E\left[\varepsilon_t \varepsilon'_t | y_1, ..., y_{t-1}, z_1, ..., z_{t-1}\right] = I \end{aligned} \tag{3.15}$$

Let A_0 be the coefficients for the contemporaneous relationships between the variables. These describe the relations within the variables to each other in each time period. Existence outside of the relationships in the past quarter is explained by the A_l lag coefficients. We assume that there is a non-singular matrix in the contemporaneous coefficient matrix for the structural model. Restriction on the elements of the respective variables of A_0 to be zero implies they are unrelated contemporaneously. The reduced form of the SVAR model can be found by post-multiplying through A_0^{-1}, that is, as follows:

$$\begin{array}{c} y'_t A_0 A_0^{-1} = \sum_{l=1}^{p} Y'_{t-l} A_l A_0^{-1} + z'_t D A_0^{-1} + \varepsilon'_t A_0^{-1} \\ y'_t = \sum_{l=1}^{p} Y'_{t-l} B_l + z'_t \Gamma + \varepsilon'_t A_0^{-1} \end{array} \tag{3.16}$$

The cross-product of the reduced form innovations stands for the error covariance matrix, which is

$$\Sigma = E\left[\left(\varepsilon'_t A_0^{-1}\right)\left(\varepsilon'_t A_0^{-1}\right)'\right] = \left[A_0 A'_0\right]^{-1} \tag{3.17}$$

When the specification of the identity matrix is used to express the meaning of the restrictions on the contemporaneous parameters in A_0, it implies that the shocks hit each equation in the contemporaneous specification. For instance, if the identity matrix is defined as in the following table, then the restriction of the corresponding A_0 is

$Variables$	$Eq1$	$Eq2$	$Eq3$
$Var.1$	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 (the second column); and shocks in variable 3 hit the third equation (the third column). In general, the reduced form A_0^{-1} is to be set as a restriction which is a just-identified triangular matrix (by the use of a Cholesky decomposition ofΣ), which implies contemporaneous causal chain among the equations. We used a maximum likelihood method to estimate the reduced form parameters of the model.

Blanchard and Quah [13], Bernanke [14], and Sims [6] suggested that, for SVARs, we could set the A_0 to be non- restriction and over-identified. Therefore, the estimation should be used with the maximum likelihood procedure to estimate the non- restriction contemporaneous relationships in the parameters of A_0. This is so that this method can use the reduced form residual covariance Σ to estimate the elements of A_0.

In the estimation using the Bayesian approach, the reduced form covariance Σ is found to have $[m \times (m+1)]/2$ free parameters. Thus, A_0 can have no more than $[m \times (m+1)]/2$ free parameters. Models are called over-identified when A_0 has fewer than $[m \times (m+1)]/2$ free parameters, or equivalent to or more than $[m \times (m+1)]/2$ zero restrictions.

Sims and Zha [7] and Waggoner and Zha [10] suggested the prior for the model for each equation. The prior in the model is illustrated by the setting

$$y'_t A_0 = x'_t F + \varepsilon'_t \tag{3.18}$$

where $x'_t = \left[y'_{t-1} ... y'_{t-p}, z'_t\right]$, $F' = [A'_1 ... A'_p D']$ are the variable matrices and the coefficients for the SVAR model. The general form of this prior is

$$a_i \sim N\left(0, \bar{S}_i\right) \; and \; f_i | a_i \sim N\left(\bar{P}_i a_i, \bar{H}_i\right), \tag{3.19}$$

where $\bar{S}_i$ is an $m \times m$ prior covariance of the contemporaneous parameters and $\bar{H}_i$ is the $k \times k$ prior covariance of the parameters in $f_i|a_i$. The prior means of a_i are zero in the structural model, while the random walk component is in $\bar{P}_i a_i$. According to the discussion by Waggoner and Zha [10] , the Bayesian prior is constructed for the unrestricted VAR model and then mapped into the restricted prior parameter space.

3.1.4 Time Varying Parameter-Vector Autoregression with Stochastic Volatility

We extend our study to the TVP-VAR with stochastic volatility model in order to capture the potential time-varying nature of the underlying structure in the rubber market in a flexible and robust manner. Thus, the model allows the shift in the parameters over time. Following Nakajima [15] and Del Negro and Primiceri [16] , the time-varying VAR model can be written as

$$Y_t = c_t + \sum_{i=1}^{P} \beta_{i,t} Y_{t-p} + A_t^{-1}\varepsilon_t, \quad \varepsilon_t\,\tilde{}\,N(0, \Sigma_{t,1}) \tag{3.20}$$

Time varying equation is

$$\beta_{i,t} = F\beta_{i,t-1} + u_t, \qquad u_t\,\tilde{}\,N(0, \Sigma_2) \tag{3.21}$$

Stochastic volatility equation is

$$\Sigma_{t,1} = \gamma \exp(h_t)\ , h_{t+1} = \phi h_{t+1} + \eta_t, \qquad \eta_t\,\tilde{}\,N(0, \Sigma_3) \tag{3.22}$$

where Y_t is a vector of endogenous variables; c_t is vector of constant term, $\beta_{i,t}$ is a matrix of time varying parameters; A_t is a lower triangular matrix with ones on the main diagonal and time varying parameters below it, $\Sigma_{1,t}$ is matrix of time varying standard deviation; $\varepsilon_t$is error of the mean equation; F is coefficient of time varying ,$\beta_{i,t-1}$; u_t , is error of the time varying equation; h_t is stochastic volatility and η_t is error of the stochastic volatility equation, We assume that $\gamma > 0$. To estimate these parameters, the Bayesian estimation through Gibbs sampler is conducted in this study. (see, Nakajima [15] and Del Negro and Primiceri [16]).

4 Results

To find the long run relationships among export prices of the rubber variable, we used a monthly data set of the export prices of rubber from Indonesia, Malaysia, Thailand, and Vietnam during the period from January, 2008 to November, 2015. All of them were considered in terms of the growth rate of the price: Indonesia (INDO), Malaysia (MAL), Thailand (TH), and Vietnam (VIET). Data regarding all of the variables were collected from the web site www.faostat.org. In addition, we checked the unit root of all the variables by conducting an ADF-test which showed that all variables are stationary in level or I(0). Then, we checked the order of lag of the variables using the LR test statistic (each test at 5% level) and the Bayesian information criterion. The results indicate that lag 1 is significant.

There are two steps to specifying a BSVAR model. First, we identified the contemporaneous relationships among the variables in A_0. We separated them into two forms, one in a restriction form and the other, a non- restriction form. We believe that in the non- restriction form, the restrictions for the information are in the price variables. The growth rates of the export price of the rubber in all the countries under investigation have a contemporaneous effect in each of the markets. Brandt and Freeman [17] interpret the structure of the contemporaneous relationships that we used to identify the A_0 matrix, which is given in Table 1. 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 1s) are contemporaneous structural relationships to be estimated while the empty cells are constrained to be zero. These empty cells in Table 1 show the absence of any contemporaneous impact of the row variables on the column equation. Finally, Σ has $[4 \times (4+1)]/2 = 10$ free parameters, and the A_0 matrix in Table 1 has 10 free parameters in the restriction form but 9 free parameters in the non- restriction form. Hence, it is evident that A_0 is over-identified for non- restriction.

Table 1: Restriction and Non- Restriction A_0

	Restriction				Non- Restriction			
Variable	Equation				Equation			
	TH	MAL	VIET	VIET	TH	MAL	INDO	VIET
TH	1	1	1	1	1	1	1	
MAL	1	1	1	1		1	1	
INDO	1	1	1	1	1		1	
VIET	1	1	1	1			1	1

The second step is to choose values for the hyper-parameters that reflect generally accepted beliefs about the dynamics of the market. The beliefs are specified by the hyper-parameters. The priors are summarized in Table 2. From the data in Table 2, we can conclude that the variables are stationary (that λ_1 is large) in terms of growth rate because it is based on log marginal density. As model 8 provides the greatest value in the log marginal density, we chose this hyper-parameter set for the model. The estimated result of the best fit model is provided in Table 3. We observe that rubber export price in each country is significantly affected by its own previous months level except for Indonesia and Malaysia. Indonesia seems to be affected by other countries thus the movement of Indonesia rubber price is influenced by Thai, Malaysia and Vietnam rubber export prices. We, then, adopted an impulse response study to analyze the reaction of any dynamic system in response to external change of export price in each country without any restriction. To generate this impulse response function, we adopted model 1 which has the highest value of marginal density when compared with the other non-restriction models (Model 3, 5, and 7). The results of the impulse response for model 1 are plotted in Figure 1. Figure 1 presents the responses of the growth rate of the price of rubber equations to shocks in the variables of the growth rates of the price of rubber in each country. Each row gives the responses of the equation for a shock in the column variable. Responses are median estimates with 68% confidence region error bands, computed point wise over a 5 months time horizon. Furthermore, we extend our proposed method, TVP-VAR with stochastic volatility model, to investigate the relationship of rubber export prices among the most influential rubber exporting countries namely Thailand, Vietnam, Indonesia, and Malaysia. This model allows us to capture asymmetry effects through a time-varying beta (coefficient). The effect of export price for each country is shown in Figures 1-4 for Thailand, Malaysia, Indonesia, and Vietnam, respectively. Finally, in Figure 5, the responses of the prices of rubber in all the countries to shocks in their prices for over 5 months are illustrated.

Table 2: Eight BSVAR Prior and Their Posterior Fit Measures

	Model 1	Model 2	Model 3	Model 4
parameters	Non- Restriction	Restriction	Non- Restriction	Restriction
lambda0	0.8	0.8	0.7	0.7
lambda1	0.1	0.1	0.05	0.05
lambda3	1	1	0	0
lambda4	0.1	0.1	0.15	0.15
lambda5	0.05	0.05	0.07	0.07
mu5	5	5	5	5
mu6	5	5	5	5
Log MD	428.2176	534.3899	329.7337	510.0159
	Model 5	Model 6	Model 7	Model 8
parameters	Non- Restriction	Restriction	Non- Restriction	Restriction
lambda0	0.9	0.9	1	1
lambda1	0.2	0.2	1	1
lambda3	2	2	1	1
lambda4	0.5	0.5	1	1
lambda5	0.07	0.07	1	1
mu5	0	0	1	1
mu6	5	5	1	1
Log MD	277.0467	573.8365	278.6259	677.8371

Source: Calculation Note: MD = Marginal density : BVAR at lag 1 is perfer in this study since the model presents a lowest BIC.

For a shock occurring in the growth rate of the rubber nat dry price in Indonesia, Malaysia, and Thailand, only the growth rates of the rubber price in Indonesia and Thailand converse to equilibrium in the long run. As for Malaysia and Vietnam, their rubber prices seem to have long run equilibrium, but they move in a manner diverse from equilibrium when it becomes over 5 months. Moreover, the maximum variance in the growth rate of the rubber price movement among all these countries comes from the shock occurrence in Thailand. For the shock occurrence of the growth rate of the rubber price in Vietnam, the growth rates of the rubber prices in all the countries develop an adjustment to long run equilibrium after 2 months. When doing an analysis based on individual country case, Indonesia and Thailand have more efficiency when it comes to adjustment of their rubber prices than Malaysia and Vietnam. But, the government of Thailand should concentrate on the control variance of their price movement because the effect of the shock occurrence in Thailand is far-reaching and brings about a large variance movement in all the other countries. So, if there is a shock occurring, the government of Thailand should quickly intervene in the rubber market for the purpose of controlling the interval of price movement or issuing the rule for controlling the price. As for Malaysia and Vietnam, their governments should be most concerned, and should quickly intervene when there is movement of price due to the occurrence of a shock and should take quick action before the shock can take its toll in all the other countries.

Table 3: Estimated result

Variable	Non- Restriction Equation			
	TH	MAL	INDO	VIET
TH	18.5351 (5.2051)	-1.2825 (9.4041)	14.5656 (6.9071)	
MAL		-13.4017 (12.8696)	13.6077 (8.8246)	
INDO	-19.1729 (5.6861)		-7.8953 (12.8191)	
VIET			0.6896 (1.1799)	1.4548 (0.1036)

Source : Calculation; () is standard error

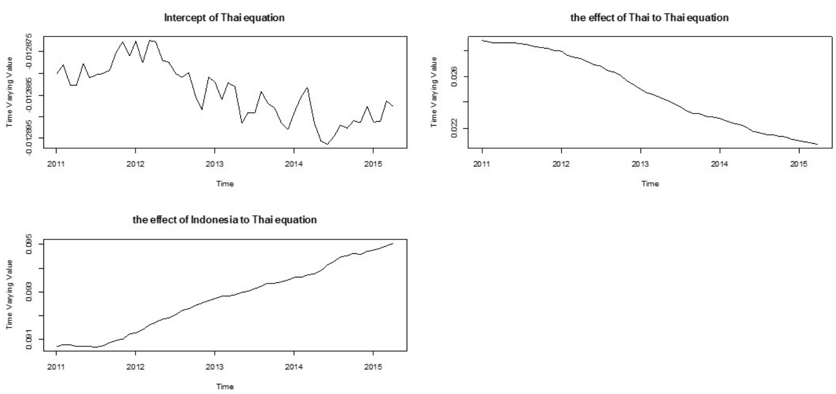

Figure 1: Time Varying Thai equation

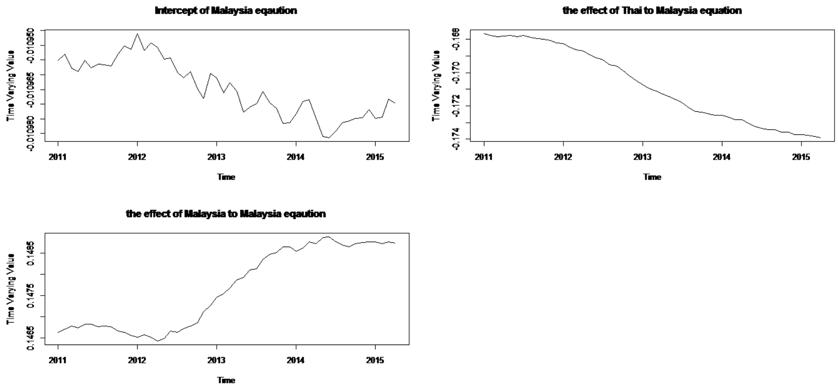

Figure 2: Time Varying Malaysia equation

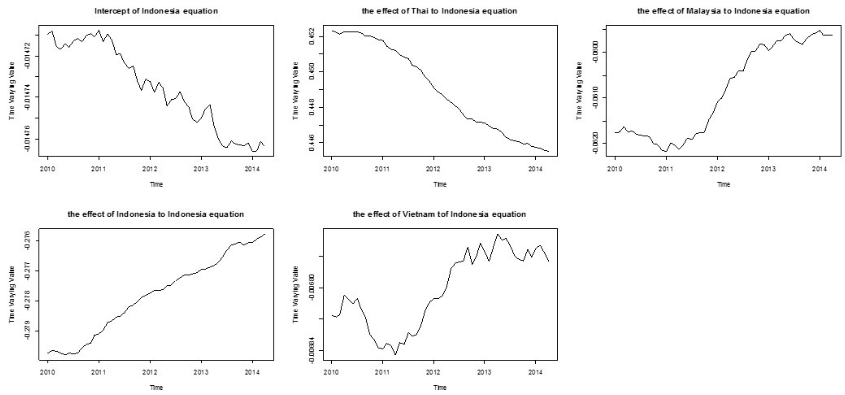

Figure 3: Time Varying Indonesia equation

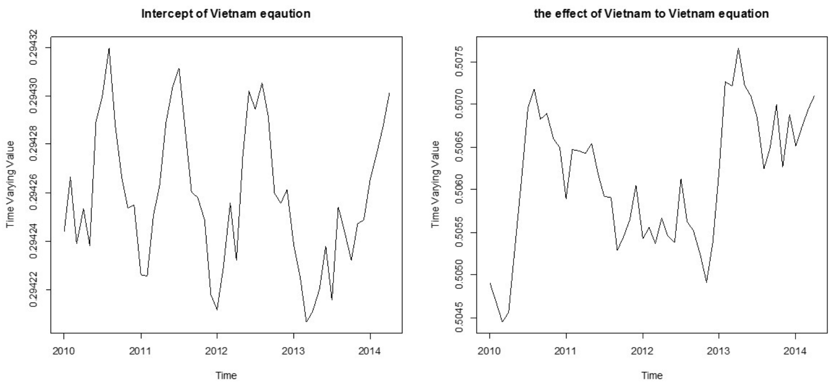

Figure 4: Time Varying Vietnam equation

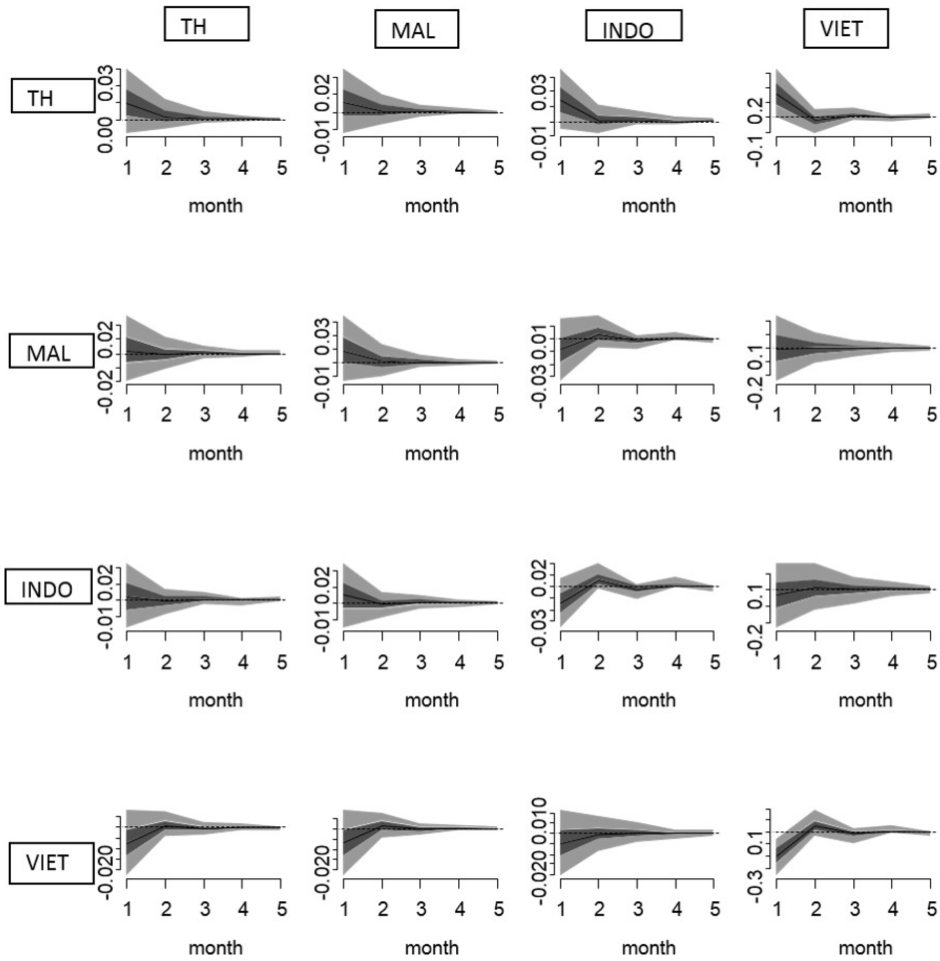

Figure 5: Impulse responses of rubber price variables to shocks over 5 months. a plot showing the 5, 25, 50, 75 and 95 percent quantiles of the simulated impulse responses.

5 Conclusion

Bayesian VAR models are able to handle large unrestricted VARs. Thus, we can analyze structural VARs that contain many variables of the rubber price in the ASEAN region. Our belief in 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 an annual data set of the export price of rubber from Indonesia, Malaysia, Thailand, and Vietnam during the period from January 2008 to November 2015, where all of them are in terms of the growth rates of the prices: Indonesia (INDO), Malaysia (MAL), Thailand (TH), and Vietnam (VIET). Data regarding all the variables were collected from the web site www.faostat.org. In addition, we checked the unit root of all the variables by conducting an ADF-test which showed all sets of time series to be stationary in level or I(0).

We considered various sets of hyper-parameters. The result shows that based on marginal density model 8 is the best-fitting model in our study. In the analysis of impulse response, it became evident that the growth rate of rubber price converses to the long run equilibrium a phenomenon that occurs only in Indonesia and Thailand. Malaysia and Vietnam both seem to have a long run equilibrium price, but after 5 months they move in a manner diverse from the equilibrium. Moreover, the maximum variance in price movement is caused from a shock occurrence in Thailand, from among all the countries. Furthermore, all the countries have an adjustment to the long run equilibrium after 2 months when a shock occurs in Vietnam.

Indonesia and Thailand are more efficient in bringing about adjustments to their rubber prices. As far as Thailand is concerned, the government of Thailand should control the interval of price movement or issue some rule such as setting a ceiling and a floor price, or applying stock management. As for the governments of Malaysia and Vietnam, they should be concerned with the long run equilibrium. Thus, they should carefully monitor not just the other countries when a shock occurs.

Further studies on this subject should include additional factors with regard to the policy variables, such as the period of government subsidy or fiscal policy. Moreover, nonlinear VAR models should be compared to BSVAR because the time series variables behave in a fluctuating manner.

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