



Analyzing the Effect of Time-Varying Factors for Thai Rice Export

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Abstract : This paper analyses the time-varying behaviors of some specific factors that affect the Thai rice export. We introduce the Markov switching regression with time-varying method as a contribution to a discussion on this issue. This model employs the Bayesian approach to do the parameter estimation of this model while Kalman filter is applied to predict the time-varying coefficient in each regime. The result shows that the proposed model is able to capture the real economic situation very well and can beat the conventional static Markov switching regression.

Keywords : Thai rice; time-varying coefficient; Markov Switching; Bayesian estimation.

2010 Mathematics Subject Classification : 47H09; 47H10.

1 Introduction

Rice is one of the most important agricultural commodities of Thailand. It has a power to influence the country's export sector since around 30% of Thailand's primary agricultural exports are taken by rice (Bank of Thailand, 2015). Moreover in terms of employment, almost one-fourth of the total population in Thailand is farmers. Therefore, the rice export plays a crucial role in Thailand's economy in terms of its contribution to economic values and employment. Additionally,

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Thailand can perform as the top three largest rice exporters in the world; therefore, a change in the export volume of Thai rice brings about a large impact on the global market at least on the world's total supply of rice. However, Thai rice export can also be affected by several factors outside the country especially the rice prices of competing countries such as Vietnam, Pakistan, and India which vary across the time. This issue deserves a special attention due to the importance of Thai rice in the international trade. Many researches have been undertaken in order to understand the factors affecting Thai rice export, and so is the attempt of this paper.

Many papers have dealt with a nonlinear behavior in economic time series data, and so this paper. A real data of the export quantity of Thai rice during January 2007 through September 2015 is plotted through Figure 1. We can see that the movement observed from the raw data perhaps has movement not rectilinear (See Figure1, top). Then, we transform the raw data to growth rate (See Figure1, bottom) and see that the series still has a nonlinear behavior in the structure. It moves either up or down. Therefore, we suspect that this data may have a nonlinear behavior. Such suspicion was taken first by Hamilton [1] whether it was an autoregressive process which has structural change in parameters called Markov Switching (MS). To explore our doubt, we employ a method of the Bayesian model comparison called Bayes factor. It is the method of model selection based which is conducted as a statistical test to compare a variety of different models. We employ the Bayes factor to decide which model between linear model and switching model is best-fit to the rice data. We consider the linear model to be a null model denoted by M_1 and the switching model to be an alternative model denoted by M_2 . More specifically, Bayes factor BF is given by

$$BF = \frac{\Pr(D|M_1)}{\Pr(D|M_2)} = \frac{\int \Pr(\theta_1|M_1) \Pr(D|\theta_1, M_1) d\theta_1}{\int \Pr(\theta_2|M_2) \Pr(D|\theta_2, M_2) d\theta_2}, \quad (1.1)$$

where $\Pr(D|M_1)$ and $\Pr(D|M_2)$ are the posterior density of the null model and alternative model, respectively. Using the Bayes factor formula, the result shown in table 1 provides the value of Bayes factor of these two models in which we find that the value of BF is equal to 0.8628. This result means the model M_2 (switching model) is more anecdotal supported by the data under consideration than the model M_1 (linear model), and hence, the data is more likely to have the nonlinear structure.

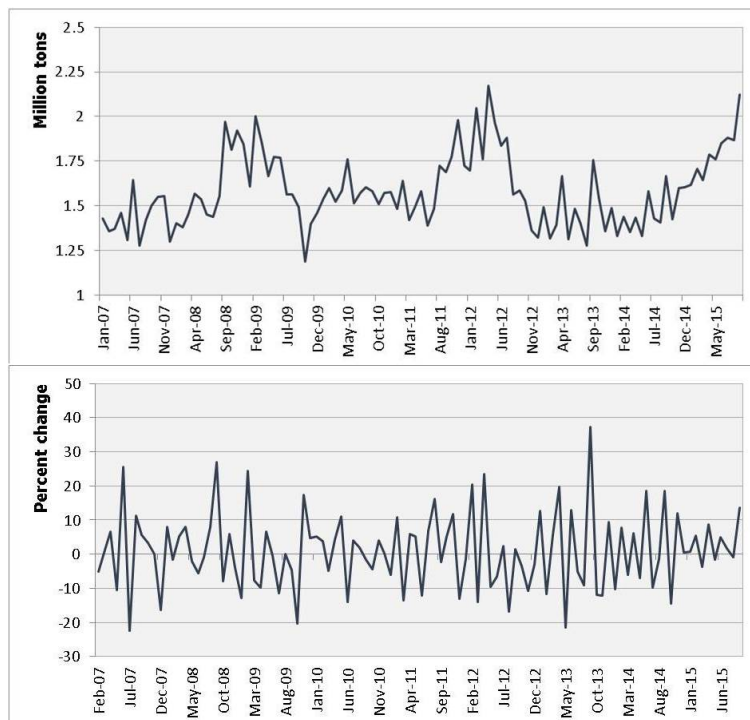
Table 1: Bayes Factor

Model	$\Pr(D M_1)$	BF	Interpretation
M_1	82.7718	0.8628	Anecdotal evidence for M_1
M_2	95.9269		

What is new in this paper? The Markov switching approach has been applied to several models such as regressions, VARs and cointegration for mod-

eling the structural changes in the data based on those models. The use of the Markov switching approach is to let parameters be state-dependent which is useful for capturing the nonlinear behavior of the data. However, the conventional model still has a limitation; the parameters based on this approach are constant over time, which in turn makes the estimated parameters unrealistic especially for the parameters of agricultural commodity prices. To deal with this problem, this paper considers the approach suggested by Kim and Nelson [2] and Kim [3]; that is the State-space models with regime-switching. This idea has spilled over empirical researches such as the works of Diebold et al. [4], Filardo [5] and more recently in Kang [6]. However, what they have done just to allow the transition probability matrix to vary over time. To the best of our knowledge, the time-varying coefficients based on the Markov switching model have not been reached before. Therefore, we consider the case that the coefficients are varying across the time by applying the Kalman filter to predict the time-varying coefficients of the system.

Figure 1: The export quantity of Thai rice from January 2007 to September 2015 in million tons (Top) and the growth rate version (Bottom)



This paper considers the time varying coefficients for Thai rice export because the factors affecting the export of Thai rice are outside the country, particularly exchange rate and rice prices of other countries. They might vary over time owing

to changes in global economy, in market sentiment and in environment. We claim that it might be better to allow for time-variation of coefficients so that we can investigate the impacts of these factors on Thai rice export more precisely.

The organization of this paper is as follows. Section 2 explains the methodology used in this paper to achieve our goal that is the Markov switching regression with time variation in coefficients. It is determined by employing Kalman filter to estimate predictive regressions for Thai rice export. To achieve this purpose we, then, apply Bayesian approach in estimation since it allows us to model the time-varying coefficients following a random walk. Section 3 presents the data used in this study. Section 4 discusses the result we obtain from the model, and presents the comparison between our results and those of conventional Markov switching regression model which is not time-varying. Finally, Section 5 concludes.

2 Methodology

In this section, we will explain about the Markov switching regression with time-varying coefficients as well as the algorithm that is used to predict the time-varying coefficients for our analysis. In addition, as we employ the Bayesian estimation to estimate our model, the prior distribution and the posterior will be discussed thoroughly in the end of this section.

2.1 Markov Switching Regression with Time-Varying Coefficients

Since West and Harrison [7] proposed the time-varying model in 1997, the model has been commonly used to capture heterogeneous dynamics of data over time. This paper extends the time-varying model to Markov switching model of Hamilton [1] and purposes a Markov switching regression with time-varying coefficients. Before we discuss about the model, let consider the general linear regression with time-varying of the form:

$$y_t = \alpha_t + \beta_t X'_t + \varepsilon_t \quad (2.1)$$

$$\begin{aligned} \alpha_t &= P_t \alpha_{t-1} + u_t \\ \beta_t &= F_t \beta_{t-1} + v_t \end{aligned} \quad (2.2)$$

where y_t is a vector of dependent variable, X'_t is a matrix of independent variables. α_t and β_t are unobserved time-varying intercept and coefficient, respectively. The disturbance ε_t is observational errors; u_t and v_t are evolutionary errors in which all of them are assumed to be normally distributed; $N(0, \sigma_\varepsilon^2)$, $N(0, \sigma_u^2)$, and $N(0, \sigma_v^2)$. In addition, ε_t , u_t , and v_t are assumed to be independent. We are aware that the time-varying equations (see Eq.2.2) imply that the coefficients follow the AR(1) process. Allowing for time-varying regression parameters, the variance of time-varying equation cannot be constant over time. Thus, we can say that if σ_v^2 and σ_u^2 are zero; the time-varying equation does not exist. The Matrix P_t and F_t are the coefficients of time-varying equation for intercept and coefficient terms.

In this study, we postulate that the number of regime or state is two namely, low growth market and high growth market, in order to basically cover a basic state of the economy Thus, Eq.(2.1) and Eq.(2.2) can be rewritten in the Markov switching form as:

$$y_t = \alpha_{(S_t)} + \beta_{t,(S_t)}X'_t + \varepsilon_t \quad (2.3)$$

where $\alpha_{(S_t)}$ and $\beta_{t,(S_t)}$ are regime dependent parameters, which are allowed to vary over time according to these following equations.

$$\begin{aligned} (\alpha_{(S_t),t+1} - \bar{\alpha}_{(S_t)}) &= P_{t,(S_t)}(\alpha_{t,(S_t)} - \bar{\alpha}_{t,(S_t)}) + u_{t+1} \\ (\beta_{(S_t),t+1} - \bar{\beta}_{(S_t)}) &= F_{t,(S_t)}(\beta_{t,(S_t)} - \bar{\beta}_{t,(S_t)}) + v_{t+1}. \end{aligned} \quad (2.4)$$

These two equations are the time-varying equations in which the term $\bar{\beta}_{t,(S_t)}$ and $\bar{\alpha}_{t,(S_t)}$ are the average of the steady state coefficient vector and intercept term, respectively, which are regime dependent. Following Hamilton [8], let $\tilde{\beta}_{t,(S_t)} = (\beta_{t,(S_t)} - \bar{\beta}_{(S_t)})$ and $\tilde{\alpha}_{t,(S_t)} = (\alpha_{t,(S_t)} - \bar{\alpha}_{(S_t)})$, thus, we can rewrite Eq.(2.3) as

$$y_t = \bar{\alpha}_{(S_t)} + \alpha_{(S_t)} + \tilde{\beta}_{t,(S_t)}X'_{t,(S_t)} + \beta_{t,(S_t)}X'_{t,(S_t)} + \varepsilon_t \quad (2.5)$$

where the term S_t represents a state variable which is governed by the first order Markov chain. Then the transition probability (Q) can be defined by $p_{ij} = \Pr(S_{t+1} = j | S_t = i)$ and $\sum_{j=1}^k p_{ij} = 1 \quad i, j = 1, \dots, k$, where p_{ij} is the probability of regime i followed by regime j , and it is convenient to collect all transition probabilities in the transition matrix Q ,

$$Q = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{k1} \\ p_{12} & p_{22} & \cdots & p_{k2} \\ \vdots & \vdots & \cdots & \vdots \\ p_{1k} & p_{2k} & \cdots & p_{kk} \end{bmatrix}. \quad (2.6)$$

2.2 The Kalman Filter and Estimation of Parameter

Kalman filter is a recursive procedure used to estimate an unobserved parameter $\theta_{(S_t)} = (\alpha_{(S_t)}, \beta_{(S_t)})$ based on the available information in the data set (ψ). Briefly, the Kalman filter consists of 2 steps estimation:

1. Prediction: In this step, the prediction of y_t is based on y_{t-1} , where y_{t-1} is computed from the expectation of $E[\beta_{(S_t)} | \psi_{t-1}]$ and $E[\alpha_{(S_t)} | \psi_{t-1}]$.

2. Updating: Updating the inference about the state vector incorporating Kalman gain matrix and the prediction error. Once y_t is realized at the end of time t , the prediction error can be computed by $v_{t-1} = y_t - y_{t|t-1}$. Then $\beta_{(S_t)}$ based on ψ_t can be estimated by the following form:

$$\beta_{(S_t)_t|t} = \beta_{(S_t)_t|t-1} + W_{t(S_t)}v_{t|t-1} \quad (2.7)$$

where $W_{(S_t)}$ is a weight assigned to new information about $\beta_{(S_t)}$ and $\alpha_{(S_t)}$ contained in the predicted error. Then, repeat step 1. (See Kim [3])

2.3 Prior Distribution and the Posterior

In this study, we use the Normal distribution for prior probability $G \sim N(\tilde{G}, \sigma_{\tilde{G}})$, Inverse gamma prior for sigma $\sigma_v^2 \sim IW(c/2, d/2)$, where $c/2$ and $d/2$ are the shape parameter and scale parameter, respectively. The weak Dirichlet priors with preference for staying in its own regime is chosen for the transition probabilities $\tilde{Q} \sim \text{Dirichlet}(q_1, q_2, q_3)$, where q_i is the scale parameter. Then, the Gibbs sampling is used to run the sampler for 10,000 iterations, with a burn-in of 2,000 iterations. Finally, 8,000 estimated parameter sets are sum, and then to be divided by 8,000 in order to obtain the estimated mean parameters of the set and get $\hat{\varsigma}$ and \hat{G} . The posterior estimation can be computed by combining these priors with the likelihood function using Bayes theorem as follows:

Posterior probability \propto likelihood \times Prior probability.

Let $\Theta_{t,(S_t)} = \{\alpha_{t,(S_t)}, \beta_{t,(S_t)}\}$, $\varsigma = \{\sigma_{v1}^2, \dots, \sigma_{vk}^2, Q\}$, $G = \{P_{(S_t)}, F_{(S_t)}\}$ and $\eta_t = \{u_t, v_t\}$, Thus the Markov switching linear regression with time-varying can be written in the following form:

$$\begin{aligned} y_t &= \bar{\alpha}_{(S_t)} + \bar{\beta}_{(S_t)} X'_{t,(S_t)} + \Theta_{t,(S_t)} X'_{t,(S_t)} + \varepsilon_t, \\ \Theta_t &= G\Theta_{t-1} + \eta_t. \end{aligned} \quad (2.8)$$

Thus, the posterior probability becomes

$$P(\varsigma, \Theta, G | y_t, X_t) \propto P(y_t, X_t | \varsigma, \Theta, G) P(\varsigma, \Theta, G), \quad (2.9)$$

where $P(\varsigma, G)$ denotes the prior of ς and G ; and $P(y_t, X_t | \varsigma, \Theta_{(S_t)}, G)$ is a likelihood function which can be formed in the log transformed function as

$$\ln L = -\frac{1}{2} \sum_{t=1}^T \ln(2\pi |f_{t|t-1}|) - \frac{1}{2} \eta'_{t|t-1} f_{t|t-1}^{-1} \eta_{t|t-1}. \quad (2.10)$$

Following Miguel and Gary [9] and Kim and Nelson [2], the Gibbs sampling algorithm is conducted to draw the parameter set, Θ and G . To estimate each parameter, the block optimization is employed. In addition, to sample the initial values, we prefer the Gibbs sampler in which the procedures are as follows: First, we draw $\tilde{\varsigma}$ from $p(\varsigma_1 | y_t, S_t, \Theta_{t,(S_t)})$. Second, we draw \tilde{G} from $p(G | y_t, S_t, \varsigma_t, \Theta_{t,(S_t)})$ using the algorithm of Chan and Jeliakov [10]. The last step is drawing \tilde{S}_t from $p(S_t | y_t, G_t, \Theta_{t,(S_t)}, \varsigma)$ using the Baum-Hamilton-Lee-Kim (BHLK) filter. Then we obtain the filter probabilities and use the standard forward-filter-backward-sample algorithm to draw the matrix of regimes.

3 Data

The data used in this paper is the data set related to Thai rice export consisting of the export quantity of Thai rice (Q_t^{export}), Thai rice export prices (P_t^{export}),

exchange rate (ER_t), Vietnamese rice export prices (P_t^{Viet}), and Indian rice export prices (P_t^{India}). The data set is monthly data collected from January 2007 to September 2015, covering 104 observations. Then we transform the data into the growth rates before estimation. More specifically, we consider the Markov switching with time varying regression of the following form

$$Q_t^{\text{export}} = \beta_{0,t,(S_t)} + \beta_{1,t,(S_t)}P_t^{\text{export}} + \beta_{2,t,(S_t)}ER_t + \beta_{3,t,(S_t)}P_t^{\text{Viet}} + \beta_{4,t,(S_t)}P_t^{\text{India}} + \varepsilon_{t,(S_t)}. \quad (3.1)$$

The coefficients $\beta = \{\beta_0, \beta_1, \beta_2, \beta_3, \beta_4\}$ are state-dependent (S_t) and time-varying (t). The distribution of ε_t is assumed to be independent and identically distributed with zero mean and positive variance. Prior to estimation, we check the stationarity of the data set using the Bayes factor testing as proposed in Wang and Ghosh [11]. The testing procedure for the unit root test is the same as for the Augmented Dickey-Fuller test thus the testing model is given by

$$\Delta y_t = \alpha_0 + (1 - \theta)y_t + \sum_{i=1}^P \Delta^2 y_{t-p}. \quad (3.2)$$

In frequentist statistics, the testing null hypothesis $H_0 : \theta = 1$ versus alternative hypothesis $H_1 : \theta < 1$, but here we change the conventional test by considering the hypothesizes H_0 and H_1 as a model M_0 and M_1 regarding Bayes factor which can be written as

$$BF = \frac{P(M_0 | y_t)}{P(M_1 | y_t)} = \frac{P(\theta = 1 | y_t)}{P(0 < \theta < 1 | y_t)}, \quad (3.3)$$

where $P(M_0 | y_t)$ and $P(M_1 | y_t)$ are the marginal likelihood of the data under the null model and the alternative model, respectively. To check whether or not the unit-root test based on the Bayes factor rejects the null hypothesis, in this study considers the null hypothesis to be rejected if Bayes factor is less than 1.

Table 2: Unit Root Test

Variable	Bayes Factor	Result
Q_t^{export}	0.9995	stationary
P_t^{export}	0.9999	stationary
ER_t	0.9999	stationary
P_t^{Viet}	0.9993	stationary
P_t^{India}	0.9999	stationary

Table 2 shows that the value of Bayes factor of all variables are less than 1. Thus, the growth rate of all variables rejects the hypothesis (model $P(\theta = 1 | y_t)$) and accepts $P(0 < \theta < 1 | y_t)$, meaning that all of them are stationary and we can continue using this data in the modeling.

4 Empirical Study

In this section, we show the estimates of the relationship between the export quantities of Thai rice and some specific factors including Thai rice export prices, exchange rate, Vietnamese rice export prices, and Indian rice export prices. The results are obtained from two different algorithms that are the static Markov switching regression and the Markov switching regression with time-varying coefficients which is our proposal. We consider these two algorithms since we aim to compare the result obtained from our model with the result obtained from the conventional model.

4.1 The Estimate of the Static Markov Switching Regression

This part is conducted for one important reason that is to compare with our time-varying coefficient model. The estimated parameters of the static Markov switching regression are shown in Table 3. This paper considers two regimes models consisting of the low growth market denoted by Regime 1 and the high growth market denoted by Regime 2. The result shows that intercept terms are statistically significant and differ from one regime to another. In Regime 1, only the parameters of exchange rate and Indian rice prices are statistically significant at 5%. It means if the exchange rate changes, say drops by 1%, it will cause an increase in Thai rice export 1.7917%.

Table 3: Estimate of the Static MS Regression

Regime 1					
Variable	Estimate	SD	2.50%	97.50%	
Intercept	-0.0997	0.0124	-3.2991	1.5715	
P_t^{export}	-0.0234	0.0269	-0.0751	-0.0045	
ER_t	-1.7917	0.7484	-2.3940	0.0961	
P_t^{Viet}	0.0870	0.1536	-0.6811	0.8551	
P_t^{India}	1.1772	0.584	-0.3806	2.6150	
Residual Standard Error = 0.0494					
Regime 2					
Variable	Estimate	SD	2.50%	97.50%	
Intercept	0.0063	0.0106	-0.0153	0.0261	
P_t^{export}	-0.3430	0.1788	-0.5663	0.1015	
ER_t	-0.9851	0.6388	-2.1473	0.5567	
P_t^{Viet}	0.2724	0.1609	-0.0588	0.4900	
P_t^{India}	1.1010	0.5324	0.1350	2.3809	
Residual Standard Error = 0.0853					

Note: BIC= -98.9869

As well as the coefficient of Indian rice price which is positive, implying that the higher the Indian export prices, say 1%, the higher export demand for Thai rice by 1.1772%. In Regime 2, the parameters of almost all variables are statistically significant except the exchange rate. Thai rice export price is statistically significant where its coefficient has negative sign following the theory of demand. The parameters of Indian and Vietnamese rice prices are also statistically significant, meaning that the increase in Indian and Vietnamese export prices by 1% can cause the increase in export demand for Thai rice by 1.1010% and 0.2724% respectively.

The transition probability matrix of the model is presented in Table 4. The estimated probability means the conditional probability based on the information available throughout the whole sample period at future date t . The result shows that the probability of switching from Regime 1 (low growth market) to Regime 2 (high growth market) is 0.2149, while remaining in Regime 1 is 0.7851. On the other hand, the probability of switching from Regime 2 to Regime 1 is 0.2551, while remaining in Regime 2 is 0.7449.

Table 4: Transition Probability Matrix (Static MS Regression)

	Regime1	Regime2
Regime1	0.7851	0.2149
Regime2	0.2551	0.7449

4.2 The Estimate of the MS Regression with Time-Varying Coefficients

This section provides the benchmark result of this paper that is the estimate of the Markov switching (MS) regression with time-varying coefficients. Figure 2 displays the result of time-varying coefficients according to our analysis. Here, we have four variables of interest comprising Thai rice export prices, exchange rate, Vietnamese rice export prices, and Indian rice export prices. The market is separated into two states which are the low growth (Regime 1) and the high growth (Regime 2) regarding fluctuations in the market. The results of filtered probabilities are shown in Figure 3. The probability values vary between 0 and 1, and then the observation is classified in the Regime 1 if $\Pr(S_t = 1 | y_t) > 0.5$ and in the Regime 2 if $\Pr(S_t = 1 | y_t) \leq 0.5$ [1]. A transition probability matrix presented in Table 5 shows that there is somewhat symmetry probability of remaining in Regime 1 (0.7993) and Regime 2 (0.7860), quite the similar as the probability values of the MS regression model shown in Table 4. Despite this, the Bayesian information criterion (BIC) values clearly indicate that time-varying MS regression provides a better fit than static MS regression. The BIC value of the static MS regression model based on this data set is equal to -98.9869 while the BIC value of the time-varying one is -100.5605.

Table 5: Transition Probability Matrix (Time-varying MS Regression)

	Regime1	Regime2
Regime1	0.7993	0.2140
Regime2	0.2007	0.7860

Note: BIC= -100.5605

The contributions of this paper can be expressed through Figure 2 where the coefficients of those variables are varying over time. Figure 2 shows a relationship between the export quantity of Thai rice and those explanatory variables. Even if the Markov switching gives us the ability to capture different market movement in different states/regimes, the coefficients of those variables in each state still appear to be not constant over time. Instead, they seem to jump out of the line during January 2008-2009. Therefore, using the conventional mean-regression to describe this relationship may not be consistent and reasonably accurate. Here, we study the time variation of coefficients and we found that our proposed model can capture the real economic situation very well. In October 2007, India banned non-basmati rice exports. It caused the lower supply of rice in global market, and then the rice price in the world market was increased as the rice market is oligopolistic. Therefore, the rice exports trended to switch to the high growth market state due to this event. From a view of an economic interpretation, during that time, a change in export price would create a large impact on the export since the market was more sensitive to price than it actually is. The time-varying coefficient of Thai rice export price shown in Figure 2 (Top left) conforms to this event and so do the performance of coefficients of Vietnamese (Bottom left) and Indian (Bottom right) rice prices.

5 Conclusion

This paper considers the factors affecting Thai rice export with time variation of the coefficients. The variables of interest consist of Thai rice export prices, exchange rate, and also rice prices of main competitors in the market, i.e. Vietnam and India. We introduce the Markov switching regression with time-varying coefficients as a contribution to the discussion on the factors affecting Thai rice export. We estimate the model using Bayesian estimator while the Kalman filter is applied to predict the time-varying coefficient in each regime. We compare the result obtained from our proposed model with the conventional model, the static Markov switching regression model estimated by MLE. We found that the proposed model is able to capture the real economic situation very well especially the crucial time in 2007. It can illustrate the high correlation among the export quantities of Thai rice and those considerable variables during that time while the conventional model is not able to capture this situation. The static time-invariant

Figure 2: Time-varying coefficients of Export price (Top left), Exchange rate (Top right), Vietnamese Price (Bottom left), and Indian Price (Bottom right)

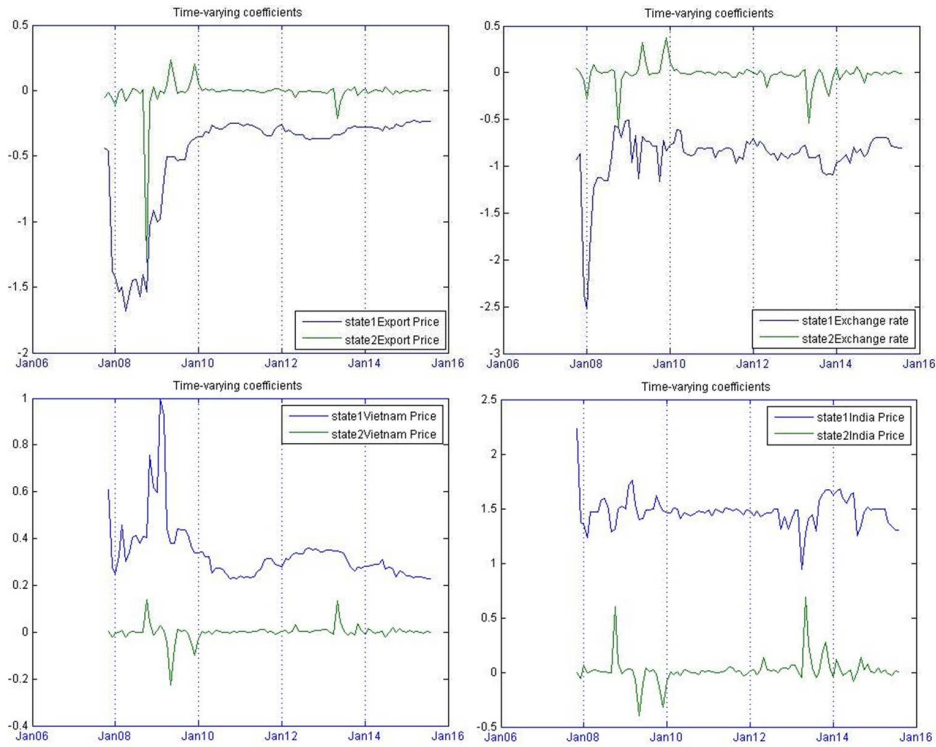
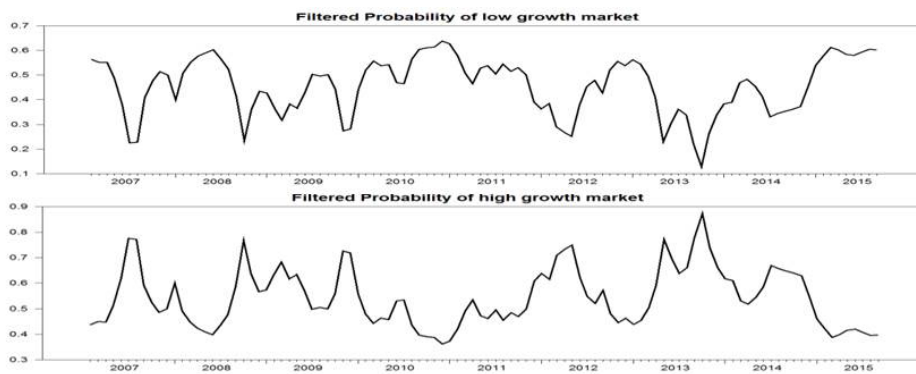


Figure 3: Filtered probabilities of low growth market (Top) and high growth market (Bottom)



regression is only able to examine the existence of this relationship only on mean and be constant over time. Therefore, this paper suggest considering the use of the Markov switching regression with time-varying coefficients when we have to deal with the data with high fluctuation because it can capture movement over time of the coefficients appropriately. Finally, one issue that should be addressed for the future work is to check the robustness of the proposed model. Moreover, it would be challenging if we could extend this model to a vector autoregressive model.

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