Volatility Model with Markov Regime Switching to Forecast Baht/USD

N. Sopipan, A. Intarasit, K. Chuarkham

***Abstract*—**In this paper, we forecast the volatility of Baht/USDs using Markov Regime Switching GARCH (MRS-GARCH) models. These models allow volatility to have different dynamics according to unobserved regime variables. The main purpose of this paper is to find out whether MRS-GARCH models are an improvement on the GARCH type models in terms of modeling and forecasting Baht/USD volatility. The MRS-GARCH is the best performance model for Baht/USD volatility in short term but the GARCH model is best perform for long term.

***Keywords*—**Volatility, Markov Regime Switching, Forecasting.

I. Introduction

THE characteristic that all financial markets have in common is uncertainty, which is related to their short and long-term price state. This feature is undesirable for the investor but it is also unavoidable whenever the financial market is selected as the investment tool. The best that one can do is to try to reduce this uncertainty. Financial market forecasting (or Prediction) is one of the instruments in this process.

In time series, a financial price is a transformation to log return series for a stationary process. Mehmet [1] states that financial returns have *three characteristics*. The first is *volatility clustering* that means large changes tend to be followed by large changes and small changes tend to be followed by small changes. Second is *fat tailedness* (excess kurtosis) which means that financial returns often display a fatter tail than a standard normal distribution and the third is *leverage effect* which means that negative returns result in higher volatility than positive returns of the same size.

However, exchange rate volatility modeling is important in the framework of international trade due to two main reasons. Firstly, national governments have realized the impact of this volatility on their own monetary policies and this has been more so for countries where economic growth is driven by export growth. Thus exchange rate fluctuations are regularly monitored by central banks for macroeconomic analysis and market surveillance purposes. Secondly, due to the increasing number of international portfolios, investors and corporate managers have realized that there is an ever increasing need to address risk in the context of exchange rate volatility.

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Finance practitioners have largely avoided volatility modeling and forecasting in the higher dimensional situations of practical relevance, relying instead on the generalized autoregressive conditional heteroskedasticity (GARCH) volatility modeling.

The GARCH models mainly capture three characteristics of financial returns. The development of GARCH type models was started by Engle [2]. Engle introduced ARCH to model heteroskedasticity by relating the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past. Bollerslev [3] generalized the ARCH (GARCH) model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of disturbance.

Hamilton and Susmel [4] stated that the spurious high persistence problem in GARCH type models can be solved by combining the Markov Regime Switching (MRS) model with ARCH models (SWARCH). The idea behind regime switching models is that as market conditions change, the factors that influence volatility also change.

In this paper, we use GARCH and MRS-GARCH models to forecast the volatility of currency in Thai Baht against U.S. Dollar (Baht/USD) and to compare their performance. Finally, we forecast a closing price for Baht/USD for both the short term and the long term.

In the next section, we present the MRS-GARCH model. The empirical methodology and model estimation results are given in Section III. In Section IV, statistical loss functions are described and the out-of-sample forecasting performance of various models is discussed and we apply the forecasting price to the Baht/USD for both the short term and the long term. The conclusion is given in Section VI.

II. Markov Regime Switching of GARCH Model

Let $\{P_t\}$ denote the series of the financial price at time t and $\{r_t\}_{t>0}$ be a sequence of random variables on a probability space (Ω, F, P). For index t denotes the daily closing observations and $t = -R+1,...,n$. The sample period consists of an estimation (or in-sample) period with R observations $(t = -R+1,...,0)$, and an evolution (or out-of-sample) period with n observations $(t = 1,...,n)$, let r_t be the logarithmic return (in percent) on the financial price at time t, i.e.

$$r_t = 100 \cdot \ln(\frac{P_t}{P_{t-1}}) \quad (1)$$

The GARCH (1,1) model for the series of the returns r_t can be written as

$$r_t = \delta + \varepsilon_t = \delta + \eta_t \sqrt{h_t}$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$$

where $\alpha_0 > 0, \alpha_1 \ge 0$ and $\beta_1 \ge 0$ are assumed to be non-negative real constants to ensure that $h_t \ge 0$. We assume η_t is an i.i.d. process with zero mean and unit variance.

The parameters of the GARCH model are generally considered as constants. But the movement of financial returns between recession and expansion is different, and may result in differences in volatility. Gray [5] extended the GARCH model to the MRS-GARCH model in order to capture regime changes in volatility with unobservable state variables. It was assumed that those unobservable state variables satisfy the first order Markov Chain process.

The MRS-GARCH model with only two regimes can be represented as follows:

$$r_t = \delta_{S_t} + \varepsilon_t = \delta_{S_t} + \eta_t \sqrt{h_{t,S_t}} \quad (2)$$

and $h_{t,S_t} = \alpha_{0,S_t} + \alpha_{1,S_t} \varepsilon_{t-1}^2 + \beta_{1,S_t} h_{t-1}$

where $S_t = 1$ or 2, δ_{S_t} is the mean and h_{t,S_t} is the volatility under regime S_t on F_{t-1}, both are measurable functions of $F_{t-\tau}$ for $\tau \le t-1$. In order to ensure easily the positive of conditional variance we impose the restrictions $\alpha_{0,S_t} > 0$, $\alpha_{1,S_t} \ge 0$ and $\beta_{1,S_t} \ge 0$. The sum $\alpha_{1,S_t} + \beta_{1,S_t}$ measures the persistence of a shock to the conditional variance.

The unobserved regime variable S_t is governed by a first order Markov Chain with constant transition probabilities given by

$$\Pr(S_t = i \mid S_{t-1} = j) = p_{ji} \quad \text{for } i, j = 1,2 \quad (3)$$

In matrix notation,

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix} = \begin{bmatrix} p & 1-q \\ 1-p & q \end{bmatrix} \quad (4)$$

In MRS-GARCH model with two regimes, Klaassen [6] forecast volatility for *k-step-ahead* by using the recursive method as in the standard GARCH model where k is a positive integer. In order to compute the multi-step-ahead volatility forecasts, we firstly compute a weighted average of the multi-step-ahead volatility forecasts in each regime where the weights are the prediction probability ($\Pr(S_{T+\tau} = i \mid F_{T-1})$).

Since there is no serial correlation in the returns, the *k-step-ahead* volatility forecast at time T depends on information at time *T-1*. Let $\hat{h}_{T,T+k}$ denote the time T aggregated volatility forecasts for the next k steps. It can be calculated as follows: (See, for example [7])

$$\hat{h}_{T,T+k} = \sum_{\tau=1}^{k} \hat{h}_{T,T+\tau} = \sum_{\tau=1}^{k} \left[\sum_{i=1}^{2} \Pr\left(S_{T+\tau} = i \mid F_{T-1}\right) \hat{h}_{T,T+\tau,S_{T+\tau}=i} \right] \quad (5)$$

where $\hat{h}_{T,T+\tau,S_{T+\tau}=i}$ indicates the τ*-step-ahead* volatility forecast in regime i made at time T and can be calculated recursively as follows: (See, [8])

$$\begin{aligned} \hat{h}_{T,T+\tau,S_{T+\tau}=i} &= E_{T-1}\left(\hat{h}_{T+\tau-1} \mid S_{T+\tau} = i\right) \\ &= \alpha_{0,S_{T+\tau}=i} + \alpha_{1,S_{T+\tau}=i} E_{T-1}\left(\varepsilon_{T+\tau-1}^2 \mid S_{T+\tau} = i\right) \\ &\quad + \beta_{1,S_{T+\tau}=i} E_{T-1}\left(h_{T+\tau-1} \mid S_{T+\tau} = i\right) \\ &= \alpha_{0,S_{T+\tau}=i} + \left(\alpha_{1,S_{T+\tau}=i} + \beta_{1,S_{T+\tau}=i}\right) E_{T-1}\left(h_{T,T+\tau-1} \mid S_{T+\tau} = i\right) \end{aligned} \quad (6)$$

Also, in generally the prediction probability in (5) is computed as

$$\begin{bmatrix} \Pr\left(S_{T+\tau} = 1 \mid F_{T-1}\right) \\ \Pr\left(S_{T+\tau} = 2 \mid F_{T-1}\right) \end{bmatrix} = P^{\tau+1} \cdot \begin{bmatrix} \Pr\left(S_{T-1} = 1 \mid F_{T-1}\right) \\ \Pr\left(S_{T-1} = 2 \mid F_{T-1}\right) \end{bmatrix},$$

where P defined in (4) and $\Pr(S_{T-1} = i \mid F_{T-1})$ will be discussed in (11). Lastly, we compute expectation part $E_{T-1}(h_{T,T+\tau-1} \mid S_{T+\tau} = i)$ in (6) as follows:

$$\begin{aligned} E_{T-1}(h_{T,T+\tau-1} \mid S_{T+\tau} = i) &= E\left[h_{T+\tau-1} \mid S_{T+\tau} = i, F_{T-1}\right] \\ &= E\begin{bmatrix} E[r_{T+\tau-1}^2 \mid S_{T+\tau-1} = j, F_{T-1}] \\ -\left[E[r_{T+\tau-1} \mid S_{T+\tau-1} = j, F_{T-1}]\right]^2 \mid S_{T+\tau} = i, F_{T-1} \end{bmatrix} \\ &= E\left[E[r_{T+\tau-1}^2 \mid S_{T+\tau-1} = j, F_{T-1}] \mid S_{T+\tau} = i, F_{T-1}\right] \\ &\quad - E\left[\left[E[r_{T+\tau-1} \mid S_{T+\tau-1} = j, F_{T-1}]\right]^2 \mid S_{T+\tau} = i, F_{T-1}\right] \end{aligned} \quad (7)$$

where

$$\begin{aligned} &E\left[E[r_{T+\tau-1}^2 \mid S_{T+\tau-1} = j, F_{T-1}] \mid S_{T+\tau} = i, F_{T-1}\right] \\ &= \sum_{j=1}^{2} \begin{Bmatrix} E[\delta_{T+\tau-1}^2 + 2\delta_{T+\tau-1}\varepsilon_{T+\tau-1} + \varepsilon_{T+\tau-1}^2 \mid S_{T+\tau-1} = j, F_{T-1}] \\ \cdot \Pr\left[S_{T+\tau-1} = j \mid S_{T+\tau} = i, F_{T-1}\right] \end{Bmatrix} \\ &= \sum_{j=1}^{2} \hat{p}_{ji,T-1}\left[\delta_{T+\tau-1,S_{T+\tau-1}=j}^2 + h_{T+\tau-1,S_{T+\tau-1}=j}\right] \end{aligned} \quad (8)$$

where

$$\begin{aligned} \hat{p}_{ji,T-1} &= \Pr\left(S_{T+\tau-1} = j \mid S_{T+\tau} = i, F_{T-1}\right) \\ &= \frac{p_{ji} \Pr\left(S_{T+\tau-1} = j \mid F_{T-1}\right)}{\Pr\left(S_{T+\tau} = i \mid F_{T-1}\right)} \end{aligned} \quad (9)$$

Similarly, we computed in the second term of the right hand side in (7) such that

$$E\left[\left[E[r_{T+\tau-1}\left|S_{T+\tau-1}=j,F_{T-1}\right.]\right]^2\left|S_{T+\tau}=i,F_{T-1}\right.\right] = \sum_{j=1}^{2}\tilde{p}_{ji,T-1}\left[\delta_{T+\tau-1,S_{T+\tau-1}=j}\right]^2 \quad (10)$$

substitutes both (8) and (10) to (7) such that

$$E_{T-1}(\hat{h}_{T,T+\tau-1}\left|S_{T+\tau}=i\right.) = \sum_{j=1}^{2}\tilde{p}_{ji,T-1}\left[\delta^2_{T+\tau-1,S_{T+\tau-1}=j}+h_{T+\tau-1,S_{T+\tau-1}=j}\right]-\sum_{j=1}^{2}\tilde{p}_{ji,T-1}\left[\delta_{T+\tau-1,S_{T+\tau-1}=j}\right]^2$$

In the next step, we will compute those regime probabilities $p_{it}=\Pr(S_t=i\left|F_{t-1}\right.)$ for $i=1,2$ in (9). Note that when the regime probabilities are based on information up to time *t*, we describe this as filtered probability ($\Pr(S_t=i\left|F_t\right.)$).

In order to compute the regime probabilities, we denote $f_{1t}:=f(r_t\left|S_t=1,F_{t-1}\right.)$, $f_{2t}:=f(r_t\left|S_t=2,F_{t-1}\right.)$. Then, the conditional distribution of return series r_t becomes a mixture-of-distribution models in which mixing variables are regime probability p_{it} . That is

$$r_t\left|F_{t-1}\right. \sim \begin{cases} f(r_t\left|S_t=1,F_{t-1}\right.) & \text{with probability } p_{1t} \\ f(r_t\left|S_t=2,F_{t-1}\right.) & \text{with probability } p_{2t}=1-p_{1t} \end{cases},$$

where $f(r_t\left|S_t,F_{t-1}\right.)$ denotes one of the assumed conditional distributions for errors: Normal Distribution (N), Student-t Distribution with only single degree of freedom (t) or double degree of freedom (2t) and Generalized error distributions (GED).

We shall compute regime probabilities recursively by following two steps (Kim and Nelson [9]):

Step 1. Given $\Pr(S_{t-1}=j\left|F_{t-1}\right.)$ at the end of the time $t-1$, the regime probabilities $p_{it}=\Pr(S_t=i\left|F_{t-1}\right.)$ are computed as

$$\Pr(S_t=i\left|F_{t-1}\right.)=\sum_{j=1}^{2}\Pr(S_t=i,S_{t-1}=j\left|F_{t-1}\right.).$$

Since the current regime (S_t) only depends on the regime one period ago (S_{t-1}), then

$$\Pr(S_t=i\left|F_{t-1}\right.)=\sum_{j=1}^{2}\Pr(S_t=i\left|S_{t-1}=j\right.)\Pr(S_{t-1}=j\left|F_{t-1}\right.) = \sum_{j=1}^{2}p_{ji}\Pr(S_{t-1}=j\left|F_{t-1}\right.)$$

Step 2. At the end of the time *t*, when the observed return at time *t* (r_t) and the information at time *t*. We set $F_t=\{F_{t-1},r_t\}$, the $\Pr(S_t=i\left|F_t\right.)$ is calculated as follows:

$$\Pr(S_t=i\left|F_t\right.)=\Pr(S_t=i\left|r_t,F_{t-1}\right.)=\frac{f(r_t,S_t=i\left|F_{t-1}\right.)}{f(r_t\left|F_{t-1}\right.)},$$

where $f(r_t,S_t=i\left|F_{t-1}\right.)$ is joint density of returns and unobserved regime at state i for $i=1,2$ variables can be written as follows:

$$f(r_t,S_t=i\left|F_{t-1}\right.)=f(r_t\left|S_t=i,F_{t-1}\right.)f(S_t=i\left|F_{t-1}\right.) = f(r_t\left|S_t=i,F_{t-1}\right.)\Pr(S_t=i\left|F_{t-1}\right.)$$

and $f(r_t\left|F_{t-1}\right.)$ is marginal density function of returns which can be constructed as follows:

$$f(r_t\left|F_{t-1}\right.)=\sum_{i=1}^{2}f(r_t,S_t=i\left|F_{t-1}\right.)=\sum_{i=1}^{2}f(r_t\left|S_t=i,F_{t-1}\right.)\Pr(S_t=i\left|F_{t-1}\right.).$$

We use Bayesian arguments

$$\Pr(S_t=i\left|F_t\right.)=\frac{f(r_t,S_t=i\left|F_{t-1}\right.)}{f(r_t\left|F_{t-1}\right.)} = \frac{f(r_t\left|S_t=i,F_{t-1}\right.)\Pr(S_t=i\left|F_{t-1}\right.)}{\sum_{i=1}^{2}f(r_t\left|S_t=i,F_{t-1}\right.)\Pr(S_t=i\left|F_{t-1}\right.)} = \frac{f_{it}p_{it}}{\sum_{i=1}^{2}f_{it}p_{it}} \quad (11)$$

Then, all regime probabilities p_{it} can be computed by iterating these two steps. However, at the beginning of iteration $\Pr(S_0=i\left|F_0\right.)$ for $i=1,2$ it is necessary to start iteration. Hamilton ([10], [11]) suggest we should use unconditional regime probabilities instead of $\Pr(S_0=i\left|F_0\right.)$. These are given by

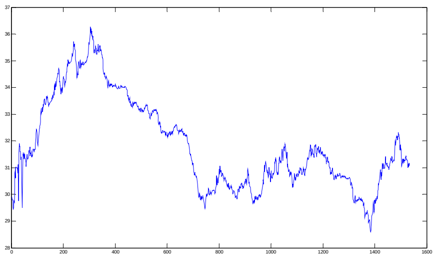
$$\Pr(S_0=1\left|F_0\right.)=\frac{1-q}{2-p-q},\Pr(S_0=2\left|F_0\right.)=\frac{1-p}{2-p-q}.$$

Given initial values for regime probabilities, conditional mean and conditional variance in each regime, the parameters of the MRS-GARCH model can be obtained by maximizing numerically the log-likelihood function. The log-likelihood function is constructed recursively similar to that in GARCH models.

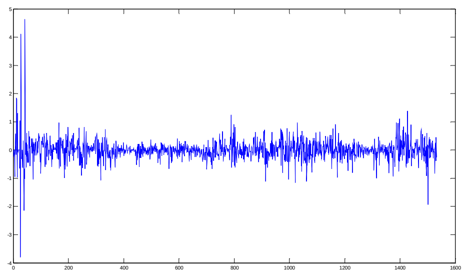
III. Empirical Methodology and Model Estimation Results

A. Data

The data set used in this study is the daily closing prices of Baht/USD (P_t) over the period 1/01/2008 through 26/10/2013 ($t=1,\ldots,1{,}532$ observations). The data set is obtained from the www.efinancethai.com. The data set is divided into in-sample ($R = 1{,}000$ observations) and out-of-sample ($n = 532$ observations). The plot of P_t and log returns series $(r_t$; (1)) are given in Fig. 1. Plot P_t and r_t displays the usual properties of financial data series.



(a) Baht/USD closing prices (P_t)



(b) log returns series (r_t)

Fig. 1 Graph of (a) Baht/USD closed prices (P_t) and (b) log returns series (r_t) for the period 1/01/2008 through 26/20/2013

As expected, volatility is not constant over time and exhibits volatility clustering with large changes in the indices often followed by large changes, and small changes often followed by small changes. Descriptive statistics of r_t are represented in Table I. As Table I shows, r_t has a positive average return of 0.074%. The daily standard deviation is 1.537%. The series also displays a negative skewness of -0.102 and an excess kurtosis of 9.457. These values indicate that the returns are not normally distributed, namely, these have fatter tails because skewness does not equal zero and kurtosis is greater than 3. Also, the Jarque-Bera test statistic of 2,107.620 confirms the non-normality of r_t and the Augmented Dickey-Fuller test of -35.873 indicates that r_t is stationary.

TABLE I
SUMMARY STATISTICS OF BAHT/USD LOG RETURNS SERIES

Statistic	Return(%)
Min	-10.823
Max	10.71
Mean	0.074
Standard deviation	1.537
Skewness	-0.102
Kurtosis	9.457
Jarque-Bera Normality test	2,107.620 (P-value= 0.000)
Augmented Dickey-Fuller test	-35.873 (P-value= 0.000)

In order to test the significance level of autocorrelation functions (ACF) in Table II, we apply the Ljung and Box Q-test. The null hypothesis of the test is that there is no serial correlation in the return series up to the specified lag. Serial correlation in the P_t is confirmed as non-stationary but r_t is stationary. Because the serial correlation in the squared returns is non-stationary this suggests conditional heteroskedasticity. Therefore, we analyze the significance of autocorrelation in the squared mean adjusted return $(r_t - \delta)^2$ series by usin the Ljung-Box Q-test. We also apply Engle's ARCH test.

B. Empirical Methodology

This empirical part adopts GARCH (1,1) and MRS-GARCH (1,1) models to estimate the volatility of P_t . In order to account for the fat tails feature of financial returns, we consider three different distributions for the innovations: Normal (N), Student-t (t) and Generalized Error Distributions (GED).

1. GARCH Models

Table III presents an estimation of the results for GARCH type models. It is clear from the table that almost all parameter estimates including δ in GARCH type models are highly significant at 1%. All models display strong persistence in volatility ranging from 0.9654 to 0.9724.

2. Markov Regime Switching GARCH Models

Estimation results and summary statistics of MRS-GARCH models are presented in Table IV. Most parameter estimates in MRS-GARCH are significantly different from zero at least at 95% confidence level. But α_0 and β_1 are insignificant in some states. All models display strong persistence in volatility, that is, volatility is likely to remain high over several price periods once it increases.

3. In-Sample Evaluation

We use various goodness-of-fit statistics to compare volatility models. These statistics are Akaike Information Criteria (AIC) Schwarz Bayesian Information Criteria (SBIC). In Table V, the results of goodness-of- fit statistics and loss functions for all volatility models are presented.

According to AIC, MRS-GARCH-GED is the best. GARCH-t is the best in SBIC and MSE2, MRS-GARCH-N is the best in MSE1. MRS-GARCH-t is the best in QLIKE, MAD2, MAD2 and HMSE. We found that different models were suitable for various loss functions.

TABLE II
ACF OF BAHT/USD CLOSING PRICES, LOG RETURNS SERIES, SQUARE RETURN AND RESULTS FOR ENGLE'S ARCH TEST

	ACF of Baht/USD closed price.			ACF of Baht/USD log return.		
Lags	ACF	LBQ Test	P-value	ACF	LBQ Test	P-value
1	1.00	1528.00	0.00	0.06	4.86	0.03
2	0.99	3048.00	0.00	-0.04	7.55	0.02
3	0.99	4560.00	0.00	-0.01	7.77	0.05
4	0.99	6064.00	0.00	-0.02	8.54	0.07
5	0.99	7560.00	0.00	-0.03	9.62	0.09
6	0.98	9048.00	0.00	0.02	10.02	0.12
7	0.98	10529.00	0.00	-0.01	10.11	0.18
8	0.98	12002.00	0.00	-0.01	10.18	0.25
9	0.97	13467.00	0.00	0.03	11.79	0.23
10	0.97	14924.00	0.00	-0.08	21.32	0.02
	ACF of Baht/USD square return.			Results for Engle's ARCH test		
Lags	ACF	LBQ Test	P-value	ARCH Test	P-value	
1	0.40	248.34	0.00	1526.20	0.00	
2	0.10	262.90	0.00	1525.20	0.00	
3	0.13	289.80	0.00	1524.30	0.00	
4	0.08	299.46	0.00	1523.20	0.00	
5	0.03	300.74	0.00	1522.20	0.00	
6	0.01	300.95	0.00	1521.20	0.00	
7	0.01	301.00	0.00	1520.30	0.00	
8	0.00	301.01	0.00	1519.30	0.00	
9	0.01	301.07	0.00	1518.30	0.00	
10	0.02	301.87	0.00	1517.30	0.00	

TABLE III
SUMMARY RESULTS OF GARCH TYPE MODELS

Parameter	GARCH		
	N	t	GED
δ	0.0026***	0.0091**	0.0034***
Std.err.	2.4317	1.6909	2.3450
α_0	0.0058***	0.0078***	0.0106***
Std.err.	13.6898	6.1297	6.1326
α_1	0.2282***	0.2332***	0.2661***
Std.err.	41.6488	7.8254	7.7171
β_1	0.7594***	0.7293***	0.6851***
Std.err.	129.5164	34.3132	26.2869
ν		3.8239***	0.9036***
Std.err.		13.7565	39.2163
Log(L)	-2087.32	-2033.89	-2038.22
Persistence	0.9724	0.9654	0.9672
LBQ(22)	32.6362	32.6362	32.6362
	(0.0672)	(0.0672)	(0.0672)
LBQ2(22)	189.92	190.07	189.83
	(0.0000)	(0.0000)	(0.0000)

*** and ** refer the significance at 99% and 95% confidence level respectively,

LBQ(22) is Ljung-Box test of innovation at lag 22, LBQ^2 (22) is Ljung-Box test of squared innovation at lag 22 and P-value for LBQ test in parentheses. Std.err is standard error

TABLE IV
SUMMARY RESULTS OF MRS-GARCH MODELS

Parameters	MRS-GARCH							
	N		t		t2		GED	
State i	Low volatility regime	High volatility regime	Low volatility regime	High volatility regime	Low volatility regime	High volatility regime	Low volatility regime	High volatility regime
$\delta^{(i)}$	0.0830**	0.1800**	0.1136***	0.1699**	0.1135***	0.1699**	0.1708**	0.1088***
Std.err.	0.0404	0.0934	0.0388	0.0766	0.0389	0.0766	0.0776	0.0369
$\alpha_0^{(i)}$	0.0137*	2.1786***	0.0111	1.6163***	0.0111	1.6152***	1.8421***	0.0126
Std.err.	0.0075	0.3353	0.0086	0.513	0.0086	0.531	0.487	0.0096
$\alpha_1^{(i)}$	0.0463***	0.3654***	0.0380**	0.3170***	0.0380**	0.3170***	0.3244***	0.0418**
Std.err.	0.0127	0.1029	0.016	0.1154	0.0161	0.1167	0.1258	0.018
$\beta_1^{(i)}$	0.9436***	0	0.9535***	0.1844	0.9535***	0.1859	0.1015	0.9485***
Std.err.	0.0151	0.1115	0.0175	0.1771	0.0175	0.1798	0.1403	0.02
p	0.9975***		0.9981***		0.9983***		0.9981***	
Std.err.	0.0023		0.0024		0.0024		0.0029	
q	0.9976***		0.9983***		0.9981***		0.9983***	
Std.err.	0.0021		0.0024		0.0024		0.0023	
$\nu^{(i)}$			6.0583***		6.0789***	6.0134***	1.3234***	
Std.err.			0.9544		1.6734	1.4119	0.0598	
Log(L)	-2050.44		-2013.2		-2017.57		-2013.22	
σ^2	1.3564	3.433	1.3059	3.2417	1.3059	3.2492	3.2087	1.3
π	0.5103	0.4897	0.4722	0.5278	0.4722	0.5278	0.5278	0.4722
Persistence	0.9899	0.3654	0.9915	0.5014	0.9915	0.5029	0.4259	0.9903
LBQ(22)	34.9963		34.9963		34.9963		34.9963	
	(0.0388)		(0.0388)		(0.0388)		(0.0388)	
$LBQ^2(22)$	178.7254		178.6977		178.7734		178.7132	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	

*** and ** refer the significance at 99% and 95% confidence level respectively, LBQ(22) is Ljung-Box test of innovation at lag 22, LBQ^2 (22) is Ljung-Box test of squared innovation at lag 22 and P-value for LBQ test in parentheses. Std.err is standard error

TABLE V
IN-SAMPLE EVALUATION RESULTS

Models	N*	AIC	SBIC	MSE1	MSE2	QLIKE	MAD2	MAD1	HMSE
GARCH-N	4	3.5089	3.5260	1.3811	50.1151	1.6646	8.4461	2.7378	0.8701
GARCH-t	5	3.4210	**3.4423**	1.3298	**48.2319**	1.6659	8.4433	2.6606	0.8611
GARCH-GED	5	3.4282	3.4496	1.3337	48.5005	1.6652	8.3971	2.6654	0.8589
MRS-GARCH-N	10	3.4571	3.4998	**1.3002**	51.2119	1.6149	8.2523	2.6546	0.8427
MRS-GARCH-t2	12	3.3980	3.4492	1.3254	55.5689	1.6152	8.2603	2.6913	0.8465
MRS-GARCH-t	11	3.4036	3.4506	1.3047	52.8737	**1.6148**	**8.2246**	**2.6602**	**0.8413**
MRS-GARCH-GED	11	**3.3963**	3.4433	1.3268	56.0621	1.6157	8.2578	2.6917	0.8461

*N=Number of Parameters.

IV. FORECASTING VOLATILITY IN OUT-OF-SAMPLE

In this section, we investigate the ability of MRS-GARCH and GARCH type models to forecast the volatility of Baht/USDs in out-of-sample.

In Table VI, we present the result of loss function of out-of-sample with forecasting volatility for one day step ahead (short term), and we found the MRS-GARCH models perform best.

In Table VII, we present the result of loss function of out-of-sample with forecasting volatility for twenty-two day step ahead (long term), and we found the GARCH models perform best.

TABLE VI
RESULT LOSS FUNCTION OF OUT-OF-SAMPLE WITH FORECASTING VOLATILITY FOR ONE DAY STEP AHEAD

Model	MSE1	MSE2	QLIKE	MAD1	MAD2	HMSE
GARCH-N	0.156	1.766	1.554	0.179	0.998	0.185
GARCH-t	0.132	1.595	1.538	**0.170**	0.763	0.181
GARCH-GED	0.133	1.606	1.539	0.167	0.765	0.182
MRS-GARCH-N	0.063	0.681	1.491	0.326	0.529	0.080
MRS-GARCH-t2	**0.055**	**0.566**	**1.487**	0.250	0.493	0.079
MRS-GARCH-t	0.056	0.585	**1.487**	0.250	**0.488**	**0.071**
MRS-GARCH-GED	0.086	0.915	1.492	0.213	0.625	0.073

TABLE VII
RESULT LOSS FUNCTION OF OUT-OF-SAMPLE WITH FORECASTING VOLATILITY FOR 22DAYS STEP AHEAD

Model	MSE1	MSE2	QLIKE	MAD1	MAD2	HMSE
GARCH-N	**0.079**	0.735	0.296	0.739	0.530	**0.493**
GARCH-t	0.835	0.263	**0.042**	**0.144**	0.600	0.931
GARCH-GED	0.731	0.984	0.521	0.449	**0.022**	0.952
MRS-GARCH-N	0.390	0.156	0.090	0.580	0.025	0.582
MRS-GARCH-t2	0.204	0.370	0.500	0.322	0.255	0.635
MRS-GARCH-t	0.834	**0.003**	0.976	0.370	0.336	0.566
MRS-GARCH-GED	0.484	0.785	0.111	0.172	0.476	0.752

V. CONCLUSION

In this paper, we forecast volatility of Baht/USDs using Markov Regime Switching GARCH (MRS-GARCH) models. These models allow volatility to have different dynamics according to unobserved regime variables.

The main purpose of this paper is to find out whether MRS-GARCH models are an improvement on the GARCH models in terms of modeling and forecasting Baht/USD closing price volatility. We compare MRS-GARCH (1,1) models with GARCH(1,1) models. All models are estimated under three distributional assumptions which are Normal, Student-t and GED. Moreover, student-t distribution which takes different degrees of freedom in each regime is considered for MRS-GARCH models.

We first analyze in-sample performance of various volatility models to determine the best form of the volatility model over the period 1/01/2008 through 26/10/2013. As expected, volatility is not constant over time and exhibits volatility clustering showing large changes in the price of an asset often followed by large changes, and small changes often followed by small changes.

We forecasted volatility for one day step ahead (short term), and we found that the MRS-GARCH models perform best. However, the result of forecasting volatility for twenty-two day step ahead (long term) showed thatthe GARCH models perform best.

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