Forecasting Volatility of Gold Price Using Markov Regime Switching and Trading Strategy

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Received October 24, 2011; revised December 1, 2011; accepted December 15, 2011

ABSTRACT

In this paper, we forecast the volatility of gold prices 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 gold price volatility. The MRS-GARCH is best performance model for gold price volatility in some loss function. Moreover, we forecast closing prices of gold price to trade future contract. MRS-GARCH got the most cumulative return same GJR model.

Keywords: Forecasting; Volatility; Gold Price; Markov Regime Switching

1. 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.

The financial market forecasting task divides researchers and academics into two groups: those who believe that we can devise mechanisms to predict the market and those who believe that the market is efficient and whenever new information comes up the market absorbs it by correcting itself, thus there is no space for prediction. Furthermore they believe that the financial market follows a random walk, which implies that the best prediction you can have about tomorrow’s value is today’s value.

In time series, a financial price transformed to log return series for stationary process which look like white noise. Mehmet [1] said financial returns have three characteristics. 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.

The generalized autoregressive conditional heteroskedasticity (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 the 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. The Exponential GARCH (EGARCH) model proposed by Nelson [4] to cope with the skewness of ten encountered in financial returns, led to GJR-GARCH which was introduced independently by Glosten, Aganathan, and Runkle [5] to account for the leverage effect.

Hamilton and Susmel [6] 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. Nowadays some researchers have development of GARCH model, as well as the benefit of using GARCH model [1, 7-9].

Gold is a precious metal which is also classed as a commodity and a monetary asset. Gold has acted as a multifaceted metal through the centuries, possessing similar characteristics to money in that it acts as a store of wealth, a medium of exchange and a unit of value. Gold has also played an important role as a precious metal with sig-
significant portfolio diversification properties. Gold is used in industrial components, jewellery and as an investment asset. The quantity of gold required is determined by the quantity demanded for industry investment and jewellery use. Therefore an increase in the quantity demanded by the industry will lead to an increase in the price of the metal.

The changing price of gold can also be the result of a change in the Central Bank’s holding of these precious metals. In addition, changes in the rate of inflation, currency markets, political harmony, equity markets, and producer and supplier hedging, all affect the price equilibrium.

Gold futures is an alternative investment tool which relies on the gold price movement. The investors can benefit from the gold futures investment by making profit from both directions, either up or down, which is like stock index futures trading. In addition, gold futures can also hedge against gold price fluctuations or stock market volatility due to the negative correlation to the stock market. This will provide a greater opportunity to make profit when the stock market declines during an economic downturn.

Gold futures in Thailand are futures contracts which rely on gold bullion with a purity of 96.5% due its popularity among buyers nationwide for gold physical trading. Gold futures trade in implement cash settlement method with no need of physical delivery.

Edel Tully, et al. [10] has investigated the Asymmetric power GARCH model has to capture the dynamics of the gold market. Results suggest that the APGARCH model provides the most adequate description for the gold market.

In this paper, we use GARCH, EGARCH, GJR-GARCH and MRS-GARCH models to forecast the volatility of gold prices and to compare their performance. Moreover we shall use this estimated volatility to forecast the closing price of gold. Finally, we apply the forecasting price of gold to trading in gold future contracts with a maturity date of August 2011 (GF10Q11).

In the next section, we present the MRS-GARCH model. Estimation and in-sample evaluation results are given in Section 3. In Section 4, statistical loss functions are described and out-of-sample forecasting performance of various models is discussed. In Section 5 we apply the forecasting price to the gold price for trading in future contracts. The conclusion is given in Section 6.

2. Markov Regime Switching of GARCH Model

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

\[
r_t = 100 \cdot \ln \left( \frac{P_t}{P_{t-1}} \right)
\]

(1)

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

\[
r_t = \delta + \varepsilon_t = \delta + \eta_t \sqrt{h_t}
\]

where \( \alpha_0 > 0, \alpha_i \geq 0 \) and \( \beta \geq 0 \) are assumed to be nonnegative real constants to ensure that \( h_t \geq 0 \). We assume \( \eta_t \) 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 [11] 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:

\[
r_t = \delta_S + \varepsilon_t = \delta_{s_1} + \eta_t \sqrt{h_{t,s_1}}
\]

(2)

and \( h_{t,s_1} = \alpha_{0,s_1} + \alpha_{1,s_1} \varepsilon_{t-1}^2 + \beta_{1,s_1} h_{t-1,s_1} \).

where \( S_t = 1 \) or 2, \( \delta_{s_1} \) is the mean and \( h_{s_1} \) is the volatility under regime \( S_t \) on \( F_{t-1} \), both are measurable functions of \( F_{t-1} \) for \( \tau \leq t-1 \). In order to ensure easily the positive of conditional variance we impose the restrictions \( \alpha_{0,s_1} > 0, \alpha_{1,s_1} \geq 0 \) and \( \beta_{1,s_1} \geq 0 \). The sum \( \alpha_{1,s_1} + \beta_{1,s_1} \) 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

\[
\text{Pr}(S_t = i | S_{t-1} = j) = p_{ji} \quad \text{for } i, j = 1, 2
\]

(3)

In matrix notation,

\[
P = \begin{bmatrix}
p_{11} & p_{21} \\
p_{12} & p_{22}
\end{bmatrix} = \begin{bmatrix}
p & 1-q \\
1-p & q
\end{bmatrix}
\]

(4)

2.1. Forecasting Volatility

In MRS-GARCH model with two regimes, Klaassen [12] 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+1} = i|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 \( \hat{h}_{T+k} \) denote the time T aggregated volatility forecasts for the next k steps. It can be calculated as follows: (See, for example Marcucci [9], page 8)

\[
\hat{h}_{T+k} = \sum_{i=1}^{k} \Pr(S_{t+1} = i|F_{t-1}) \hat{h}_{T+k, S_{t+1}=i},
\]

where \( \hat{h}_{T+k, S_{t+1}=i} \) indicates the \( \tau \)-step-ahead volatility forecast in regime \( i \) made at time \( T \) and can be calculated recursively as follows:

\[
\hat{h}_{T+k, S_{t+1}=i} = E_{T-1}(\hat{h}_{T+k-1}|S_{t+1} = i)
\]

\[
= \alpha_{0,S_{t+1}=i} + \alpha_{S_{t+1}=i} E_{T-1}(\hat{e}_{T+k-1}^2|S_{t+1} = i)
\]

\[
+ \beta_{S_{t+1}=i} E_{T-1}(\hat{h}_{T+k-1}|S_{t+1} = i)
\]

\[
= \alpha_{0,S_{t+1}=i} + \alpha_{S_{t+1}=i} E_{T-1}(E_{T-1}(\hat{e}_{T+k-1}^2|S_{t+1} = i)|S_{t+1} = i)
\]

\[
+ \beta_{S_{t+1}=i} E_{T-1}(\hat{h}_{T+k-1}|S_{t+1} = i)
\]

\[
= \alpha_{0,S_{t+1}=i} + (\alpha_{S_{t+1}=i} + \beta_{S_{t+1}=i}) E_{T-1}(h_{T+k-1}|S_{t+1} = i).
\]

(6)

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

\[
\Pr(S_{t+1} = 1|F_{t-1}) = p_{11} \Pr(S_{t+1} = 1|F_{t-1})
\]

\[
\Pr(S_{t+1} = 2|F_{t-1}) = p_{12} \Pr(S_{t+1} = 2|F_{t-1})
\]

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

\[
E_{T-1}(h_{T+k-1}|S_{t+1} = i) = E\left[ E[r_{T+k-1}|S_{t+1} = i, F_{t-1}] \right]
\]

\[
= E\left[ E[r_{T+k-1}|S_{t+1} = i, F_{t-1}] \right]
\]

\[
- E\left[ E[r_{T+k-1}|S_{t+1} = j, F_{t-1}] \right]|S_{t+1} = i, F_{t-1})
\]

\[
= E\left[ E[r_{T+k-1}|S_{t+1} = j, F_{t-1}] \right]|S_{t+1} = i, F_{t-1})
\]

where

\[
E\left[ E[r_{T+k-1}^2|S_{t+1} = j, F_{t-1}] |S_{t+1} = i, F_{t-1}) \right]
\]

\[
= \sum_{j=1}^{2} \left( E[r_{T+k-1}^2|S_{t+1} = j, F_{t-1}] \right) \cdot \Pr(S_{t+1} = j|S_{t+1} = i, F_{t-1})
\]

\[
= \sum_{j=1}^{2} \left( E\left[ (\delta_{T+k-1} + \epsilon_{T+k-1})^2 \right]|S_{t+1} = j, F_{t-1} \right)
\]

\[
\cdot \Pr(S_{t+1} = j|S_{t+1} = i, F_{t-1})
\]

\[
= \sum_{j=1}^{2} \left( E\left[ \delta_{T+k-1}^2 + 2\delta_{T+k-1}\epsilon_{T+k-1} + \epsilon_{T+k-1}^2 \right]|S_{t+1} = j, F_{t-1} \right)
\]

\[
\cdot \Pr(S_{t+1} = j|S_{t+1} = i, F_{t-1})
\]

where

\[
\tilde{p}_{i,j,1} = \Pr(S_{t+1} = j|S_{t+1} = i, F_{t-1})
\]

\[
= p_{i,j} \Pr(S_{t+1} = j|F_{t-1})
\]

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

\[
E\left[ E[r_{T+k-1}^2|S_{t+1} = j, F_{t-1}] \right]|S_{t+1} = i, F_{t-1})
\]

\[
= \sum_{j=1}^{2} \left( \tilde{p}_{i,j,1} \left( \delta_{T+k-1}^2 + h_{T+k-1, S_{t+1}=j} \right) \right)
\]

(10)

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

\[
E_{T-1}(h_{T+k-1}|S_{t+1} = i)
\]

\[
= \sum_{j=1}^{2} \tilde{p}_{i,j,1} \left( \delta_{T+k-1, S_{t+1}=j}^2 + h_{T+k-1, S_{t+1}=j} \right)
\]

In the next step, we will compute those regime probabilities \( p_{nj} = \Pr(S_{t+1} = j|F_{t-1}) \) 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+1} = i|F_{t-1})).

In order to compute the regime probabilities, we denote \( f_{j} := f(r_{j} | S_{t+1} = i, F_{t-1}) \), \( f_{i} := f(r_{i} | S_{t+1} = 2, F_{t-1}) \). Then, conditional distribution of return series \( r_{j} \) becomes a mixture-of-distribution model in which mixing variables is regime probability \( p_{nj} \). That is

\[
r_{j} | F_{t-1} = \begin{cases} f(r_{j} | S_{t+1} = 1, F_{t-1}) & \text{with probability } p_{1j} \\ f(r_{j} | S_{t+1} = 2, F_{t-1}) & \text{with probability } p_{2j} = 1 - p_{1j} \end{cases}
\]

where \( f(r_{j} | S_{t+1} = i, F_{t-1}) \) denotes one of the assumed condi-
tional 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, [13], page 63):

**Step 1:** Given \( \Pr(S_t = i|F_{t-1}) \) at the end of the time \( t-1 \), the regime probabilities \( p_i = \Pr(S_t = i|F_{t-1}) \) are computed as

\[
\Pr(S_t = i|F_{t-1}) = \frac{2}{j=1} \Pr(S_t = i,S_{t-1} = j|F_{t-1}).
\]

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

\[
\Pr(S_t = i|F_{t-1}) = \frac{2}{j=1} \Pr(S_t = i,S_{t-1} = j|F_{t-1}).
\]

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

\[
\Pr(S_t = i|F_t) = \Pr(S_t = i|r_t,F_{t-1}) = \frac{f(r_t,S_t = i|F_{t-1})}{f(r_t|F_{t-1})},
\]

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

\[
f(r_t,S_t = i|F_{t-1}) = f(r_t|S_t = i,F_{t-1}) f(S_t = i|F_{t-1})
\]

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

\[
f(r_t|F_{t-1}) = \frac{2}{j=1} f(r_t,S_t = i|F_{t-1})
\]

We use Bayesian arguments

\[
\Pr(S_t = i|F_t) = \frac{f(r_t,S_t = i|F_{t-1})}{f(r_t|F_{t-1})}
\]

\[
= \frac{f(r_t|S_t = i,F_{t-1}) \Pr(S_t = i|F_{t-1})}{\sum_{j=1}^{2} f(r_t|S_t = j,F_{t-1}) \Pr(S_t = j|F_{t-1})}
\]

\[
= \frac{f_{i0}p_i}{\sum_{j=1}^{2} f_{i0}p_j}
\]

Then, all regime probabilities \( p_i \) can be computed by iterating these two steps. However, at the beginning of iteration \( \Pr(S_0 = i|F_0) \) for \( i = 1,2 \) are necessary to start iteration. Hamilton ([14,15]) suggest we should use unconditional regime probabilities instead of \( \Pr(S_0 = i|F_0) \). These are given by

\[
\pi_i = \Pr(S_0 = 1|F_0) = \frac{1-q}{2-p-q}, \quad \pi_2 = \Pr(S_0 = 2|F_0) = \frac{1-p}{2-p-q}
\]

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.

### 2.2. Forecasting Price

We forecast financial price at \textit{k}-\textit{step-ahead} with MRS-GARCH models. Denote \( \hat{r}_{t+k} \) is \textit{k}-\textit{step-ahead} forecasting logarithm return of financial price at time \( t \) depend on \( F_{t-k} \).

We compute as:

\[
\hat{r}_{t+k} = E_{t+k}[r_{t+k}] = \sum_{j=1}^{2} \Pr(S_{t+k} = i|F_{t-1}) \hat{r}_{t+k,S_{t+k}=i} \] \tag{12}

where

\[
\hat{r}_{t+k,S_{t+k}=i} = E_{t+k}[r_{t+k}|S_{t+k} = i]
\]

\[
= E_{t+k}[\delta + e_{t+k} | S_{t+k} = i]
\]

\[
= E_{t+k}[\delta | S_{t+k} = i] + E_{t+k}[e_{t+k} | S_{t+k} = i]
\]

\[
= \sum_{j=1}^{2} \Pr(S_{t+k} = j|S_{t+k} = i,F_{t+k}) \hat{r}_{t+k,S_{t+k}=i}
\]

\[
= \sum_{j=1}^{2} p_{j,k} \delta_{S_{t+k}=i}
\]

Forecasting financial price \textit{one-step-ahead}, we use (12) and (1) combine in log-return of financial price is

\[
\hat{P}_{t+1} = P_j \cdot \exp \left[ \sum_{j=1}^{2} \Pr(S_{t+1} = i|F_{t-1}) \cdot \sum_{j=1}^{2} p_{j,k} \delta_{S_{t+k}=i} \right] \] \tag{13}

### 3. Empirical Methodology and Model Estimation Results

#### 3.1. Data

The data set used in this study is the daily closed prices of gold price \( (P) \) over the period 4/01/2007 through
The data set is obtained from the basis of the London Gold Market Fixing Limited on day and the foreign exchange rate for Baht to US dollars announced by TFEX (The Thailand Futures Exchange) on day, after conversion for weight and fineness. The data set is divided into in-sample ($R = 1192$ observations) and out-of-sample ($n = 21$ observations). The plot of $P_t$ and log returns series ($r_t$; (1)) are given in Figure 1. Plot $P_t$ and $r_t$ displays usual properties of financial data series. 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 1. As Table 1 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 it has fatter tails because skewness does not equal zero and kurtosis is greater than 3. Also, the Jarque-Bera test statistic of 2107.620 confirms the non-normality of $r_t$. And the Augmented Dickey-Fuller test of −35.873 indicates that $r_t$ is stationary.

The autocorrelation functions (ACF) test the significance level of autocorrelation in Table 2, when we apply 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 $(r_t − \bar{r})^2$ series by Ljung-Box Q-test. And apply Engle’s ARCH test.

### 3.2. Empirical Methodology

This empirical part adopts GARCH type and MRS-GARCH (1,1) models to estimate the volatility of the $P_t$. GARCH type models that will be considered as GARCH (1,1), EGARCH(1,1) and GJR-GARCH (1,1). 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).

#### 3.2.1. GARCH Type Models

Table 3 presents an estimation of the results for GARCH type models. It is clear from the table that almost all parameter estimates including $\delta$ in GARCH type models are highly significant at 1%. However, the asymmetry effect term $\xi$ in EGARCH models is significantly dif-

### Table 1. Summary statistics of Gold price log returns series ($r_t$).

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Return (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>−10.823</td>
</tr>
<tr>
<td>Max</td>
<td>10.71</td>
</tr>
<tr>
<td>Mean</td>
<td>0.074</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.537</td>
</tr>
<tr>
<td>Skewness</td>
<td>−0.102</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>9.457</td>
</tr>
<tr>
<td>Jarque-Bera Normality test</td>
<td>2107.620 (P-value = 0.000)</td>
</tr>
<tr>
<td>Augmented Dickey-Fuller test</td>
<td>−35.873 (P-value = 0.000)</td>
</tr>
</tbody>
</table>

1Jarque-Bera Normality test is a goodness-of-fit measure of departure from normality and can be used to test the null hypothesis that the data are from a normal distribution.

2Augmented Dickey-Fuller test is a test for a unit root in a time series sample, the null hypothesis of ADF test is that the series is non-stationary.

3Ljung-Box Q-test is a type of statistical test of whether any of a group of autocorrelations of a time series are different from zero.

4ARCH test is test with null hypothesis that, in the absence of ARCH components, we have $\alpha_i = 0$ for all $i = 1, 2, \cdots, q$. The alternative hypothesis is that, in the presence of ARCH components, at least one of the estimated $\alpha_i$ coefficients must be significant.
Table 2. ACF of gold price closed price \((P_t)\), log returns \((r_t)\), square return and results for Engle’s ARCH Test.

<table>
<thead>
<tr>
<th>Lags</th>
<th>ACF of Gold price closed price.</th>
<th>ACF of Gold price log return.</th>
<th>ACF of Gold price square return.</th>
<th>Results for Engle’s ARCH test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ACF LBQ Test P-value ACF LBQ Test P-value ACF LBQ Test P-value</td>
<td>ARCH Test P-value</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.994 1202.126 0.000</td>
<td>-0.035 1.473 0.225</td>
<td>0.236 67.585 0.000</td>
<td>67.675 0.000</td>
</tr>
<tr>
<td>2</td>
<td>0.988 2391.372 0.000</td>
<td>0.057 5.370 0.068</td>
<td>0.049 70.550 0.000</td>
<td>67.735 0.000</td>
</tr>
<tr>
<td>3</td>
<td>0.982 3567.530 0.000</td>
<td>0.006 5.410 0.144</td>
<td>0.050 73.579 0.000</td>
<td>69.796 0.000</td>
</tr>
<tr>
<td>4</td>
<td>0.977 4732.067 0.000</td>
<td>0.028 6.336 0.175</td>
<td>0.047 76.324 0.000</td>
<td>70.644 0.000</td>
</tr>
<tr>
<td>5</td>
<td>0.972 5885.596 0.000</td>
<td>0.022 6.948 0.225</td>
<td>0.029 77.340 0.000</td>
<td>70.695 0.000</td>
</tr>
<tr>
<td>6</td>
<td>0.966 7026.176 0.000</td>
<td>-0.062 11.578 0.072</td>
<td>0.074 83.996 0.000</td>
<td>75.784 0.000</td>
</tr>
<tr>
<td>7</td>
<td>0.960 8152.993 0.000</td>
<td>-0.023 12.206 0.094</td>
<td>0.022 84.561 0.000</td>
<td>76.115 0.000</td>
</tr>
<tr>
<td>8</td>
<td>0.954 9267.290 0.000</td>
<td>0.070 18.159 0.020</td>
<td>0.045 87.058 0.000</td>
<td>78.019 0.000</td>
</tr>
<tr>
<td>9</td>
<td>0.948 10368.939 0.000</td>
<td>-0.024 18.893 0.026</td>
<td>0.050 90.053 0.000</td>
<td>78.693 0.000</td>
</tr>
<tr>
<td>10</td>
<td>0.943 11458.607 0.000</td>
<td>-0.010 19.025 0.040</td>
<td>0.006 90.102 0.000</td>
<td>79.005 0.000</td>
</tr>
<tr>
<td>22</td>
<td>0.885 23713.861 0.000</td>
<td>-0.046 34.412 0.045</td>
<td>0.056 178.444 0.000</td>
<td>126.931 0.000</td>
</tr>
</tbody>
</table>

Table 3. Summary results of GARCH type models.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>GARCH 1,1</th>
<th>EGARCH(^\text{a})</th>
<th>GJR-GARCH(^\text{b})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\delta)</td>
<td>0.1012***</td>
<td>0.1220***</td>
<td>0.1164***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0347</td>
<td>0.0336</td>
<td>0.0315</td>
</tr>
<tr>
<td>(\alpha_1)</td>
<td>0.0567***</td>
<td>0.0686***</td>
<td>0.0629***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0099</td>
<td>0.0174</td>
<td>0.0165</td>
</tr>
<tr>
<td>(\alpha_i)</td>
<td>0.0818***</td>
<td>0.0757***</td>
<td>0.0779***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0088</td>
<td>0.0177</td>
<td>0.0168</td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>0.8906***</td>
<td>0.8897***</td>
<td>0.8893***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0091</td>
<td>0.0184</td>
<td>0.0175</td>
</tr>
<tr>
<td>(\xi)</td>
<td>0.7175***</td>
<td>0.4317***</td>
<td>0.6245***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0040</td>
<td>0.0053</td>
<td>0.0059</td>
</tr>
<tr>
<td>(\nu)</td>
<td>5.1878***</td>
<td>1.2350***</td>
<td>5.4135***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.7608</td>
<td>0.0534</td>
<td>0.8081</td>
</tr>
<tr>
<td>Log(L)</td>
<td>-2087.32</td>
<td>-2033.89</td>
<td>-2038.22</td>
</tr>
<tr>
<td>Persistence</td>
<td>0.9724</td>
<td>0.9654</td>
<td>0.9672</td>
</tr>
<tr>
<td>LBQ(22)</td>
<td>32.6362</td>
<td>32.6362</td>
<td>32.6362</td>
</tr>
<tr>
<td>LBQ(^2)(22)</td>
<td>(0.0672)</td>
<td>(0.0672)</td>
<td>(0.0672)</td>
</tr>
<tr>
<td>LBQ(^3)(22)</td>
<td>189.92</td>
<td>190.07</td>
<td>189.83</td>
</tr>
</tbody>
</table>

*** 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.

\(^a\)Model of EGARCH(1,1) is \(\ln(h_t) = \alpha_0 + \alpha \frac{\epsilon_t}{\sqrt{h_{t-1}}} + \beta \ln(h_{t-1}) + \xi \frac{\epsilon_t}{\sqrt{h_{t-1}}}\), where \(\xi\) is the asymmetry parameter to capture leverage effect.

\(^b\)Model of GJR-GARCH(1,1) is \(h_t = \alpha_0 + \alpha \epsilon_{t-1}^2 + \beta h_{t-1} + \xi \epsilon_{t-1}^2 \max(I_{\epsilon_{t-1},0},I_{\epsilon_{t-1},0})\), where \(I_{\epsilon_{t-1},0}\) is equal to one when \(\epsilon_{t-1}\) is greater than zero and another is zero.
different from zero, which indicates unexpected negative returns implying higher conditional variance as compared to same size positive returns. All models display strong persistence in volatility ranging from 0.9654 to 0.9741 unless EGARCH models are very low, that is, volatility is likely to remain high over several price periods once it increases.

3.2.2. Markov Regime Switching GARCH Models

Estimation results and summary statistics of MRS-GARCH models are presented in Table 4. Most parameter estimates in MRS-GARCH are significantly different from zero at least at 95% confidence level. But $\alpha_0$ and $\beta_1$ 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.

### 3.2.3. 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) and Log-likelihood (LOGL) values. In Table 5,

<table>
<thead>
<tr>
<th>Parameters</th>
<th>MRS-GARCH</th>
<th>GED</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N, t, 2t$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\delta^*$</td>
<td>0.0830**</td>
<td>0.1800**</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0404</td>
<td>0.0934</td>
</tr>
<tr>
<td>$\alpha^*$</td>
<td>0.0137*</td>
<td>2.1786***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0075</td>
<td>0.3353</td>
</tr>
<tr>
<td>$\omega$</td>
<td>0.0463***</td>
<td>0.3654***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0127</td>
<td>0.1029</td>
</tr>
<tr>
<td>$\beta^*$</td>
<td>0.9436***</td>
<td>0.9535***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0151</td>
<td>0.1115</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.9975***</td>
<td>0.9981***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0023</td>
<td>0.0024</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>6.0583***</td>
<td>6.0789***</td>
</tr>
<tr>
<td>Std.err.</td>
<td>0.0021</td>
<td>0.0024</td>
</tr>
<tr>
<td>Persistence</td>
<td>0.9899</td>
<td>0.3654</td>
</tr>
<tr>
<td>LBQ(22)</td>
<td>34.9963</td>
<td>34.9963</td>
</tr>
<tr>
<td>LBQ$^2$(22)</td>
<td>178.7254</td>
<td>178.7254</td>
</tr>
</tbody>
</table>

*** 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.

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Table 5. In-sample evaluation results.

<table>
<thead>
<tr>
<th>Models</th>
<th>N</th>
<th>PERS</th>
<th>AIC</th>
<th>R</th>
<th>SBIC</th>
<th>R</th>
<th>LOGL</th>
<th>R</th>
<th>MSE1</th>
<th>R</th>
<th>MSE2</th>
<th>R</th>
<th>QLIKE</th>
<th>R</th>
<th>MAD2</th>
<th>R</th>
<th>MAD1</th>
<th>R</th>
<th>HMSE</th>
<th>R</th>
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</thead>
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<tr>
<td>GARCH-N</td>
<td>4</td>
<td>0.9724</td>
<td>3.5089</td>
<td>3</td>
<td>3.5260</td>
<td>9</td>
<td>2087.32</td>
<td>10</td>
<td>1.3811</td>
<td>12</td>
<td>50.1151</td>
<td>8</td>
<td>1.6646</td>
<td>7</td>
<td>8.4461</td>
<td>13</td>
<td>2.7378</td>
<td>12</td>
<td>0.8701</td>
<td>12</td>
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<tr>
<td>GARCH-t</td>
<td>5</td>
<td>0.9654</td>
<td>3.4210</td>
<td>4</td>
<td>3.4423</td>
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<td>2033.89</td>
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<td>1.3298</td>
<td>8</td>
<td>48.2319</td>
<td>2</td>
<td>1.6659</td>
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<td>8.4433</td>
<td>12</td>
<td>2.6606</td>
<td>6</td>
<td>0.8611</td>
<td>11</td>
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<tr>
<td>GARCH-GED</td>
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<td>48.5005</td>
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<td>8.3971</td>
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<td>2.6654</td>
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<td>0.8589</td>
<td>9</td>
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<tr>
<td>EGARCH-N</td>
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<td>2370.03</td>
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<td>2.1364</td>
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<td>2.1949</td>
<td>3</td>
<td>0.7389</td>
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<td>3.6605</td>
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<td>2160.38</td>
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<td>48.3539</td>
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<td>7.1297</td>
<td>1</td>
<td>2.1945</td>
<td>2</td>
<td>0.7388</td>
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<tr>
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<td>0.9741</td>
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<td>2086.68</td>
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<td>GJR-GARCH-t</td>
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<td>GJR-GARCH-GED</td>
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<td>0.9696</td>
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<td>2037.92</td>
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<td>1.3381</td>
<td>11</td>
<td>48.6682</td>
<td>7</td>
<td>1.6641</td>
<td>6</td>
<td>8.3979</td>
<td>1</td>
<td>2.1945</td>
<td>2</td>
<td>0.7388</td>
<td>2</td>
</tr>
<tr>
<td>MRS-GARCH-N</td>
<td>10</td>
<td>0.9911</td>
<td>3.4571</td>
<td>8</td>
<td>3.4998</td>
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<td>2033.89</td>
<td>7</td>
<td>1.3896</td>
<td>13</td>
<td>50.5501</td>
<td>9</td>
<td>1.6635</td>
<td>5</td>
<td>8.4406</td>
<td>11</td>
<td>2.7520</td>
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<td>0.8706</td>
<td>13</td>
</tr>
<tr>
<td>MRS-GARCH-t</td>
<td>11</td>
<td>0.9920</td>
<td>3.4036</td>
<td>3</td>
<td>3.4506</td>
<td>6</td>
<td>2017.57</td>
<td>3</td>
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<td>52.8737</td>
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<td>1.6148</td>
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<td>8.2246</td>
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<td>2.6602</td>
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<td>0.9921</td>
<td>3.3963</td>
<td>1</td>
<td>3.4433</td>
<td>2</td>
<td>2013.22</td>
<td>2</td>
<td>1.3268</td>
<td>7</td>
<td>56.0621</td>
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<td>8.2578</td>
<td>6</td>
<td>2.6917</td>
<td>11</td>
<td>0.8461</td>
<td>6</td>
</tr>
</tbody>
</table>

N = Number of Parameters, PERS = Persistence, R = Rank.

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, MRS-GARCH-2t is the best in LOGL, EGARCH-N is the best in MSE1 and MSE2. MRS-GARCH-t is the best in QLIKE. EGARCH-GED is the best in MAD2 and EGARCH-t is the best in MAD1 and HMSE. We found that different models were suitable for various loss functions.

4. Forecasting Volatility in Out-of-Sample

In this section, we investigate the ability of MRS-GARCH and GARCH type models to forecast volatility of Gold prices from out-of-sample.

In Table 6, we present the result of loss function of out-of-sample with forecasting volatility for one day ahead, and we found the EGARCH and MRS-GARCH models perform best.

5. Trading Future Contract with Forecast Volatility and Forecast Price

The aim of this study is to evaluate the profitability of applying different models to the volatility of gold prices. We assumed the market is a perfect market and the positions in our strategy are not longer than one day as described below.

We applied the Bollinger band indicator and we used samples of 21 days from 1 to 30 August 2011 (We trade one contract in GF10Q11 series is future contract in gold price with maturity date at August 2011) to trade in one contract with day by day and we did not include settlement, return do not include cost price i.e. margin, fee charged. The net daily rate of return for long position is computed as follows:

\[
R_{t+1} = C_{t+1} - \left( O_{t+1} - m \cdot \sqrt{h_{t+1}} \right)
\]

where \( R_{t+1}, C_{t+1}, O_{t+1} \) are the return, close, open price, \( h_{t+1} \) is forecasting volatility at next day \((t+1)\) and \( m \in \mathbb{Z}^+ \) is constants.

The net daily rate of return on close position is computed as follows:

\[
R_{t+1} = O_{t+1} + m \cdot \sqrt{h_{t+1}} - C_{t+1}
\]

Table 7 shows that the cumulative of return with Markov Regime Switching the GARCH-N model and the GJR-N model give cumulative of return more than the

\[
\text{Loss functions:}
MSE = \frac{1}{n} \sum_{i=1}^{n} \left( \sigma_{i,t} - \sqrt{h_{i,t}} \right)^2, \quad \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left( \sigma_{i,t}^2 - h_{i,t} \right),
\]

\[
QLIKE = \frac{1}{n} \sum_{i=1}^{n} \left( \ln(h_{i,t}) - \sigma_{i,t}^2 \right) ,
\]

\[
MAD2 = \frac{1}{n} \sum_{i=1}^{n} \left( |h_{i,t} - \sigma_{i,t}^2| \right),
\]

\[
HMSE = \frac{1}{n} \sum_{i=1}^{n} \left( \sigma_{i,t}^2 - h_{i,t} - 1 \right)
\]
Table 6. Result loss function of out-of-sample with forecasting volatility for one day ahead.

<table>
<thead>
<tr>
<th>Model</th>
<th>MSE1</th>
<th>R</th>
<th>MSE2</th>
<th>R</th>
<th>QLIKE</th>
<th>R</th>
<th>MAD1</th>
<th>R</th>
<th>MAD2</th>
<th>R</th>
<th>HMSE</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>GARCH-N</td>
<td>0.063</td>
<td>6</td>
<td>0.681</td>
<td>6</td>
<td>1.554</td>
<td>13</td>
<td>0.179</td>
<td>3</td>
<td>0.529</td>
<td>6</td>
<td>0.185</td>
<td>10</td>
</tr>
<tr>
<td>GARCH-t</td>
<td>0.055</td>
<td>5</td>
<td>0.566</td>
<td>4</td>
<td>1.538</td>
<td>11</td>
<td>0.170</td>
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<td>4</td>
<td>0.181</td>
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<td>0.182</td>
<td>9</td>
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<tr>
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<td>4</td>
<td>0.330</td>
<td>3</td>
<td>1.537</td>
<td>10</td>
<td>0.217</td>
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<td>0.519</td>
<td>5</td>
<td>0.240</td>
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<td>0.266</td>
<td>1</td>
<td>1.525</td>
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<td>0.183</td>
<td>4</td>
<td>0.429</td>
<td>1</td>
<td>0.218</td>
<td>11</td>
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<td>0.269</td>
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<td>GJR-GARCH-N</td>
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<td>1.306</td>
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<td>1.532</td>
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<td>0.896</td>
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<td>0.129</td>
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<tr>
<td>GJR-GARCH-t</td>
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<td>10</td>
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<td>11</td>
<td>1.595</td>
<td>11</td>
<td>1.487</td>
<td>1</td>
<td>0.250</td>
<td>8</td>
<td>0.763</td>
<td>8</td>
<td>0.079</td>
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<td>MRS-GARCH-t</td>
<td>0.133</td>
<td>12</td>
<td>1.606</td>
<td>12</td>
<td>1.487</td>
<td>1</td>
<td>0.250</td>
<td>8</td>
<td>0.765</td>
<td>9</td>
<td>0.071</td>
<td>1</td>
</tr>
<tr>
<td>MRS-GARCH-GED</td>
<td>0.086</td>
<td>7</td>
<td>0.915</td>
<td>7</td>
<td>1.492</td>
<td>4</td>
<td>0.213</td>
<td>6</td>
<td>0.625</td>
<td>7</td>
<td>0.073</td>
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Table 7. Cumulative Return of trading future contract of gold price with $m = 30$ between 1 to 30 August 2011.

<table>
<thead>
<tr>
<th>Date with Trading</th>
<th>GARCH</th>
<th>EGARCH</th>
<th>GJR</th>
<th>MRS-GARCH</th>
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<td>GED</td>
<td>N t</td>
<td>GED</td>
</tr>
<tr>
<td>1/8/2011</td>
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<td>-40.0</td>
<td>-40.0</td>
<td>-40.0</td>
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<td>-100.0</td>
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<td>-90.0</td>
<td>-90.0</td>
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<td>630.0</td>
<td>630.0</td>
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<tr>
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<td>710.0</td>
<td>710.0</td>
<td>690.0</td>
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<td>740.0</td>
<td>750.0</td>
<td>750.0</td>
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<tr>
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<td>1490.0</td>
<td>1470.0</td>
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<tr>
<td>7/8/2011</td>
<td>2530.0</td>
<td>2550.0</td>
<td>2530.0</td>
<td>2510.0</td>
</tr>
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<td>2530.0</td>
<td>2520.0</td>
<td>2500.0</td>
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<tr>
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<td>1360.0</td>
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<td>1560.0</td>
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<td>3360.0</td>
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<td>5240.0</td>
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</table>

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other models when we use \( m = 30 \).

6. Conclusions

In this paper, we forecast volatility of gold prices 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 which include GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) in terms of modeling and forecasting gold price closed price volatility. We compare MRS-GARCH (1,1) models with GARCH (1,1), EGARCH (1,1), GJR-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 4/01/2007 through 30/08/2011. 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.

Descriptive statistics of return series are represented by returns with fatter tails. The Augmented Dickey-Fuller test indicates gold price log returns are stationary. Serial correlation in the gold price confirms it is non-stationary but serial log returns of gold price are stationary. Serial correlation in the squared returns suggests conditional heteroskedasticity. This empirical part adopts GARCH type and MRS-GARCH models to estimate the volatility of the gold price. In order to account for fat tailed features of financial returns, we consider three different distributions for the innovations. Almost all parameter estimates in GARCH type models are highly significant at 1%. Most parameter estimates in MRS-GARCH are significantly different from zero at least at 95% confidence level. However, the results of goodness-of-fit statistics and loss functions for all volatility models show different results.

The trading details we have used describe forecasts of closed price of gold price between 1/08/2011-30/08/2011 and trading in gold future contract (GF10Q11). We found the cumulative returns with the Markov Regime Switching GARCH-N (MRS-GARCH-N) model and the GJR-N model give us higher cumulative returns than the other models when we use \( m = 30 \).

For further study, three or four volatility regimes setting can be considered rather than two-volatility regimes. Also, using Markov Regime Switching with other volatility models e.g. EGARCH, GJR. In addition, the performance of MRS-GARCH models can be hedged in future for long and short positions.

7. Acknowledgements

This research is (partially) supported by the Thailand research fund BRG.

REFERENCES


