FORECASTING OF EXTREME RISK USING MARKOV-SWITCHING GARCH MODELS: EVIDENCE FROM GLOBAL ENERGY MARKETS

S. Kavitha[1], G. Mokesh Rayalu*[2], D. Pachiyappan[3], and P. Manigandan[3]

•

[1] Assistant Professor, Department of Statistics,
Periyar University, Salem – 636011, Tamil Nadu, India.
pustatkavitha@gmail.com

[2] Assistant Professor, Department of Mathematics
School of Advanced Sciences, VIT, Vellore-632 014, Tamil Nadu, India.
Corresponding author mail: mokesh.g@vit.ac.in

[3] Department of Statistics,
Periyar University, Salem – 636011, Tamil Nadu, India.
d.pachiyappan321@gmail.com, srimanigandan95@gmail.com

Abstract

This paper investigates the Markov-Switching GARCH and Single-Regime (SR) GARCH models for the extreme-risk prediction of the global energy markets. Using daily data from Jan. 2020 to July. 2022, we find the MS-GARCH-types models are appropriate for both developed and emerging energy markets because they efficiently measure the extreme risk of energy commodities in various cases. Meanwhile, the regime-switching model's capture-dynamic structures in the financial markets and this model is only better than single-regime models in terms of long position risk predicting, rather than short position risk forecasting. That is, on the downside risk predicting, it just outperforms the single regime. Through competitive models, this study examines the risk forecast of energy commodities in different conditions. The findings have strong implications for investors and policymakers in selecting the appropriate model to predict the extreme risk of energy commodities when facing asset allocation, portfolio selection, and risk management.

Keywords: MS- GARCH, extreme risk, energy markets, prediction.

I. Introduction

To ensure economic stability and improve national security, energy commodities are among the most important natural resources used by countries as inputs in transportation, industry, and many other economic sectors. Natural gas, oil, coal is the most used major energy sources [1,2]. The oil demand is rose steadily in 2018, with China and India leading its major consumption in the United States. The US, which overtook Saudi Arabia in mid-2020, is currently the world's largest oil exporter and heavy crude oil importer [3]. Natural gas consumption increased by 4.6%, which is almost half of global energy consumption. The global demand for coal energy has continued to rise for two years since 2018. The coal-driven electricity supply is very important in Asia to meet India, China, Indonesia, South and East Asia. Since natural gas and coal are the main sources of electricity and heating, an increment in the price of energy products is expected to affect household cash flow. In contrast, oil is a fundamental input for industrial production, thus severely affecting inflation rates.

The global pandemic has revealed the vulnerability of the world economy and energy commodities to external shocks. For example, the covid-19 oil demand shock triggered an estimated 10% drop in demand, leading to a more than 60% price drop from Jan. to Apr. 2020. To prevent the shock, OPEC members agreed to reduce oil production by an estimated 9.7 million b/d in Apr.2020. Also, [4] show that volatile oil prices can trigger price fluctuations in other energy products have widespread effects on the international economy. The volatility of oil prices in the 1970s attracted much interest from financial investors, academia, and policymakers as oil-importing and exporting countries became a major factor in various economic sectors. Early pioneers studied the relationship between oil prices and economic activity-demonstrating the significant impact of oil price on macroeconomic activity and the partial responsibility for the post-world war-II US recession from 1973 to 1983 [5]. There are several methods for predicting fluctuations, but the most popular literature is the GARCH models.

Since a key contribution made by [6], who generalized autoregressive conditional heteroscedasticity (GARCH) was introduced by [7], a common in modelling VaR is that GARCH-type models are related to conditional error distribution [8]. This model depends on the suitably estimated volatility. However, conventional GARCH-type specifications belonging to the single regime model are difficult to capture structural changes during economic cycles. Furthermore, by [9], the generalized Markov regime Switching-ARCH model was introduced by [10], a researcher on volatility with regimes in the financial market. A study has found that the MS-GARCH provides far superior to the single regime GARCH on the modelling volatility [11,12].

The contribution of this study is different from two recent extreme risk studies on the two-type of models [13] confirmed that the MS-GARCH-type models had improved predictive accuracy than the standard GARCH-type models on downside risk predictions for global energy commodities. First, they should mainly investigate volatility predictions between three Single Regime-GARCH models and six-types of Regime-Switching models and the just involved two quantiles of the upside Value at Risk content in the appendix. Secondly, according to descriptive analyses of return series, they consider innovations as Normal distribution, but different distributions have a major impact on the model fit, estimation of volatility, and Value at Risk calculation. Based on this point, we consider the most common and effective distributions (Normal (*N*) and student-t (*S*)) for modelling. Third, they only investigated VaR prediction, whereas we also complement ES (expected shortfall) predicting related to extreme risk. To make more reliable conclusions, this operation compares the differences in risk measures between the two types of models in depth.

Fourth, [14] used the same back testing method for evaluating forecasting performance on volatility to assess VaR prediction, whereas we use two prevalent back testing methods used by substantial scientists and researchers [15,16,17,18,19,20] in the field of risk management, to estimate the extreme risk prediction between the two models. When we read them in the global energy commodity risk prediction, we put the RS models and their SR counterparts on the same condition. These procedures ensure that the results are more reliable. As a result, our research differs from [13] and [21] regarding energy commodity risk predicting. The literature related to the risk prediction of energy commodities via the MS-GARCH model is still limited. If the RS model shows better performance in risk measures, it will be recommended to apply for portfolio optimization and risk management. Otherwise, predicting risk values may make capital allocation insufficiently efficient as policymakers and investors set up ineligible assets against market risks.

The rest of this paper is as follows. In section 2, we present the econometric methodology adopted; section 3 describes data and summaries the descriptive statistics of the global energy commodity return series. In section 4 describes estimation results, and section 5, conclusions of this paper.

2. Methodology

2.1 GJR-GARCH model

The GJR-GARCH model is given by Glosten et al. [22]. GJR-GARCH (1,1) is written as:

$$\mathrm{J}_{\mathrm{k,t}}^2 = \mu_{0,\mathrm{k}} + \alpha\lambda_{1,\mathrm{k}}^2 \mathrm{I}\{\mathrm{y}_{\mathrm{t}-1}\ {}^30\} - \beta\lambda_{2,\mathrm{k}}^2 \mathrm{I}\{\mathrm{y}_{\mathrm{t}-1} < 0\}\mathrm{y}_{\mathrm{t}-1} + \delta \mathrm{J}_{\mathrm{k,t}-1}^2 \quad (1)$$

Where the asymmetric effect is attributed to component $\lambda_{2,\mathrm{k}}^2 \mathrm{y}_{\mathrm{t}-1}$ where the parameter $\mathrm{y}_{\mathrm{t}-1} = 0$ if $\lambda_t > 0$ means shocks on volatility from bad news and $y_{t-1} = 1$ otherwise.

2.2 EGARCH model

The Exponential GARCH (EGARCH) Model of Nelson [23] is given by:

$$\mathrm{In}\left(J_{k,t}\right) = \mu_{0,k} + \alpha_{1,k}\left(\left|\eta_{k,t-1}\right| - E\left[n_{k,t-1}\ \mathrm{I}\right]\right) + \alpha_{2,k}\eta_{k,t-1} + \beta_k \mathrm{In}\left(J_{k,t-1}\right) \quad (2)$$

Where $E\left[\left|\eta_{k,t-1}\right|\right]$ is a conditional expectation on regime k, and we have $\theta_k = \left(\mu_{0,k}, \alpha_{1,k}, \alpha_{2,k}, \beta_k\right)^T$ for (k = 1, ..., K). This specification model deals with the asymmetric reaction of volatility to previous returns i.e., leverage effect [24,25]. Covariance stationary into each regime is obtained by needful that $\beta_{\mathrm{k}} > 0$.

2.3 TGARCH model

Zakoian 1994[26], introduces the Threshold GARCH (TGARCH) model specification, where the conditional volatility is an explanatory variable instead of the conditional variance. This model is given by:

$$\mathrm{J}_{\mathrm{k,t}}^{1/2} = \mu_{0,\mathrm{k}} + \left(\alpha_{1,\mathrm{k}} \mathrm{I}\{\mathrm{y}_{\mathrm{t}-1}\ {}^30\} - \alpha_{2,\mathrm{k}} \mathrm{I}\{\mathrm{y}_{\mathrm{t}-1} < 0\}\mathrm{y}_{\mathrm{t}-1} + \beta_{\mathrm{k}} \mathrm{J}_{\mathrm{k,t}-1}^{1/2} \quad (3)$$

We have $\theta = \left(\mu_{0,\mathrm{k}}, \alpha_{1,\mathrm{k}}, \alpha_{2,\mathrm{k}}, \beta_{\mathrm{k}}\right)^{\mathrm{T}}$ for (k = 1 ..., K). To ensure positivity, we needful than $\mu_{0,\mathrm{k}} > 0$, $\alpha_{1,\mathrm{k}} > 0, \alpha_{2,\mathrm{k}} > 0$ and $\beta_{\mathrm{k}} \geq 0$. Obtained by requiring that for Co-variance stationarity in each regime $\alpha_{1,\mathrm{k}}^2 + \beta_{\mathrm{k}}^2 - 2\beta_{\mathrm{k}}\left(\alpha_{1,\mathrm{k}} + \alpha_{2,\mathrm{k}}\right) \mathrm{E}\left[\eta_{\mathrm{t,k}} \mathrm{I}\left\{\eta_{\mathrm{t,k}} < 0\right\}\right] - \left(\alpha_{1,\mathrm{k}}^2 - \alpha_{2,\mathrm{k}}^2\right) \mathrm{E}\left[\eta_{\mathrm{t,k}} \mathrm{I}\left\{\eta_{\mathrm{t,k}} < 0\right\}\right] < 1$ Francq and Zakoïan [27]. The quantities of $\mathrm{E}\left[\eta_{\mathrm{t,k}} \mathrm{I}\left\{\eta_{\mathrm{t,k}} < 0\right\}\right]$ and $\mathrm{E}\left[\eta_{\mathrm{t,k}}^2 \mathrm{I}\left\{\eta_{\mathrm{t,k}} < 0\right\}\right]$ required for the conditions of co-variance stationarity in the TGARCH model [28]. We assume two different probability distributions for D(.) we use student normal (N) and student-t (S) distribution. Then explore the advantages of incorporating the skewness in our analysis by considering the standard skewed versions of N, and S obtained using the mechanism of [29] and [30]. $K \in (1,2,3)$ are the number of regimes: we label our specification SR when K = 1 and MS when K = 3.

2.4 Model Estimation

We estimate all selected models by using maximum likelihood (ML) techniques. This approach requires the estimation of the likelihood function. The first step in this process is to generate the likelihood for MS-GARCH model specifications by collecting the vector of model parameter into $\Omega \equiv (\theta_1, \xi_1, \ldots, \theta_k, \xi_k, P)$. The conditional density of y_t in a state $h_t = k$ given Ω and τ_{t-1} is denoted by $\mathrm{f}(\mathrm{y_t} \mid \mathrm{h_t} = \mathrm{k}, \Omega, \tau_{\mathrm{t}-1})$ integrating out state h_t we obtain the density of $\mathrm{y_t}$ given Ω and τ_{t-1} only. The discrete integration is obtained as

$$\mathrm{f}(\mathrm{y_t} \mid \Omega, \tau_{\mathrm{t}-1}) \equiv \sum_{\mathrm{i}}^{\mathrm{k}} \sum_{\mathrm{j}}^{\mathrm{k}} \mathrm{p_{i,j}} \delta_{\mathrm{i,t}-1} \times \mathrm{f_D}(\mathrm{y_t} \mid \mathrm{s_t} = \mathrm{j}, \Omega, \tau_{\mathrm{t}-1}) \quad (4)$$

Where $\delta_{\mathrm{i,t}-1} \equiv \mathrm{P}[\mathrm{s}_{\mathrm{t}-1} = \mathrm{i} \mid \Omega, \tau_{\mathrm{t}-1}]$ represents the filtered probability of state i at time $\mathrm{t}-1$ and where $p_{i,j}$ is the transition probability of moving from i to state j. The filtered probabilities $(\delta_{i,t}; k = 1, \dots, K; 1, \dots, T)$ are obtained via Hamilton filter. Finally, the likelihood function is obtained from Eq. (2) as follows:

$$L(\Omega \mid \tau_T) \equiv \prod_{t=1}^{T} f(y_t \mid \Omega, \tau_{t-1}) \tag{5}$$

The estimator of maximum likelihood $\hat{\Omega}$ is obtained by maximizing the algorithm of Eq (5).

2.6 Risk Measures

Value at risk is the general estimate of the maximal loss when the position declines due to market movements in the financial domain. One step forward conditional probability density with the two regimes is computed:

$$f(y_t \mid \Omega, \tau_t) \equiv \sum_{h=1}^{2} \pi_{h,t} f_D(y_t \mid s_t = k, \Omega, \tau_{t-1}) \tag{6}$$

Since, The PDF is a combination of two-regime distribution, $\pi_{h,t} = \sum_{i=1}^{2} p_{i,h} J_{i,t-1}$ where $\theta_{i,t-1} = P(s_{t-1} = i \mid \Omega, \tau_{t-1})$ is filtered probability, a one step ahead cumulative distribution function (CDF) with regimes is obtained through its conditional probability density distribution:

$$F(y_t \mid \Omega, \tau_{t-1}) \equiv \int_{-¥}^{\varepsilon_t} f(x \mid \Omega, \tau_{t-1}) dx \tag{7}$$

Where the model parameters Ω is estimation by ML in equation (7). Financial regulators utilize VaR to evaluate risks at a particular probability level. The following is how VaR is defined:

$$\begin{gathered} \Pr\,[s_t < VaR] = 1 - p \\ VaR_t^{1-p} = u_t + \hat{\rho} s_{t-1} + z_{1-p} h_t \end{gathered} \tag{8}$$

Where $VaR_{t|t-1}^{1-p}$ is represents the maximal loss of long-position and F_Z is CDF of innovations z_t.

$$\begin{gathered} F(y_t \mid \Omega, \tau_{t-1}) = F(z_t \mid \Omega, \tau_{t-1}) h_y \\ VaR_t^{1-p} = u_t + \hat{\rho} s_{t-1} + F^{-1}(1 - p \mid \Omega, \tau_{t-1}) h_t \end{gathered} \tag{9}$$

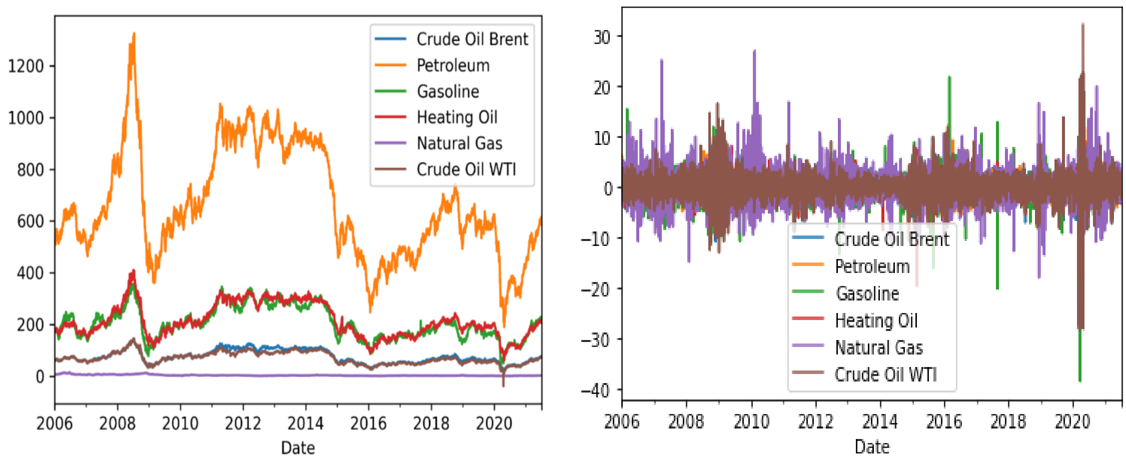
When calculating the risk of a short position, p substitutes for $1 - p$. Despite its simplicity and ease of implementation, VaR has drawbacks due to its lack of coherence as a risk measure. On the other hand, expected shortfall (ES) as measures of average losses exceeding VaR can over-come this flaw through entailing the magnitude of losses. As a result, we calculate ES to compare the predicting performance of the two types of models. ES is calculated as follows:

$$\begin{gathered} ES^{1-p} = E(s_t \mid s_t < VaR^{1-p}) \\ ES_{t|t-1}^{1-p} = \frac{1}{1-p} \int_{-\infty}^{VaR_t^{1-p}} x f(x \mid \tau_{t-1}) dx \end{gathered} \tag{10}$$

The short and long positions of VaR and ES at two quantiles are investigated in this research.

3. Data and Descriptive Statistics

This study used daily data from January 2, 2019, to July 8, 2022. Each series of datasets includes 4049 observations. The first sub-sample is used for in-sample analysis and parameter estimation, while the second sub-sample, the last 1,500 observations from the entire sample, is used for out-of-sample forecasting. The six types of energy commodities are namely, Crude oil brent, Petroleum, Gasoline, Heating oil, Natural gas, and Crude oil WTI, which are obtained from the Federal Reserve Economic Database (FRED) (https://fred.stlouisfed.org/). Energy commodity prices used in modelling, are calculated by where is the spot prices of the global energy commodity at time t. Figure 1, shows that the global energy commodity prices and returns are reported in respectively.



Graph 1: *Global energy prices*

Table .1 reports descriptive statistics for the energy price. We obtain that the mean values for Crude Oil Brent, Petroleum, Gasoline, Heating Oil, Natural Gas, and Crude Oil WTI is 0.0054%, 0.0035%, 0.0059%, 0.0046, -0.0187, and 0.0189 respectively. Meanwhile, the values of minimum and maximum have reflected the presence of small extreme returns. The estimation of unconditional volatility is through standard deviation, Natural Gas have the highest volatility.

Table 1: *Descriptive statistics of energy price*

Metrics	Crude Oil Brent	Petroleum	Gasoline	Heating Oil	Natural Gas	Crude Oil WTI
Mean	0.0054	0.0035	0.0059	0.0046	-0.0189	0.0189
Min	-27.976	-19.211	-38.535	-19.995	-18.054	-28.220
Max	19.077	13.723	22.396	10.946	26.771	31.963
Std.dev	2.305	1.955	2.656	2.079	3.203	2.655
Skewness	0.254	0.112	0.998	0.380	0.556	0.212
Kurtosis	13.753	8.473	25.923	9.319	7.729	24.806
PP test	-4328.1*	-4153.4*	-4329.9*	-4286.1*	-4126.3*	-4173.5*
ADF test	-14.092*	-14.391*	-14.265*	-15.412*	-16.037*	-14.219*
Q-(10)	27.973**	24.496**	28.306**	13.445	31.323***	30.555***
Jarque-Bera	19544***	5060.1***	89280***	6832.9***	3979.9***	80217***
ARCH-LM (10)	760***	553 ***	583***	1034***	921***	972***

Table-1 is also showing negative and positive but significant skewness for energy commodities return series which means that energy commodities return series have longer left-tails and fat-tails than the normal distribution. The kurtosis is highly significant for energy commodities return series and Gasoline display larger Kurtosis than the other return series. Values of Jarque-Bera obtained through (Jarque & Bera, 1980) depicting the rejection of normality. The significant values of Phillip Perron (PP) [31] and Augmented Dickey-Fuller (ADF)[32] test indicating that energy commodities return series are stationary. Ljung-Box is showing the (Ljung & Box, 1978) Q-statistics at 10th order for autocorrelation in raw data are extremely significant and rejecting the null hypothesis of no autocorrelation. ARCH-(1) test for restricted heteroscedasticity giving a strong indication of ARCH effect in energy commodities returns series, this evidence suggests that the usefulness and suitability of GARCH-type methods for prediction and modelling their time-varying conditional volatility. These findings usually indicate the high degree of perseverance in the conditional-volatility procedure of energy commodity prices.

4. Empirical Results

In this section, the estimation result of the MS-GARCH-type models with student normal (*N*), student-t (*S*) distribution is presented in Table 2.

4.1. In-Sample Estimation

The estimated parameters for the MS-GARCH and EGARCH models are given in Table 2. According to our results, the parameters for conditional variance are statistically significant for energy commodity prices. Almost all parameters of the EGARCH and MSGARCH (GJR-GARCH-EGARCH-TGARCH, GARCH-EGARCH, GJR-GARCH-TGARCH, EGARCH-TGARCH, GJR-GARCH, and TGARCH) models are significant, especially β_k is the leverage parameter, which implies the leverage effects of significant volatility. The energy commodity markets reveal strong evidence of asymmetric volatility, while negative news responds with strong shocks to energy commodity fluctuations. Therefore, more useful to capture the volatility of five types of energy commodities based on the two types of models. Meanwhile, Table-2 represents the transition probabilities, which mean three significant regimes volatility in the energy commodities. Therefore, the dynamic structure of energy commodities will change over periods.

Considering practical fitting capabilities, three types of criteria are used to test their appropriate performance, including Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), and log-likelihood (LL). These results reveal significant evidence of fitting efficacy for the energy commodity return series. The MS-GARCH model is successfully for Crude Oil Brent, Petroleum, Gasoline, Heating oil, and Crude Oil WTI, and it is not excellent to the counterpart in the Natural gas due to highest BIC and AIC values. Thus, these results confirm that the MS-GARCH modelling energy commodity prices dataset is appropriate and outperforms the single-regime counterpart in more cases. Nevertheless, good in-sample model fits may not generate accurate and predictions of reliable risk.

Table 2: *Modelling volatilities of energy commodity price by using MS-GARCH*

Global energy markets	**Crude Oil Brent**	**Petroleum**	**Gasoline**	**Heating Oil**	**Natural Gas**	**Crude Oil WTI**
Models (Regime-3)	GJR-GARCH-TGARCH	GARCH-EGARCH	GJR-GARCH -TGARCH	EGARCH-TGARCH	GJR-GARCH	TGARCH
Regime-1 μ_1	0 .0001 (0.000)***	0.0011 (0.001)**	0.0108 (0.010)**	0.0137 (0.007)**	0.2958(0.188)**	0.1003 (0.041)**
α_1	0.0562 (0.000)***	0.0014 (0.001)**	0.0032 (0.004)**	0.0100 (0.008)**	0.0161(0.016)**	0.0134 (0.013)**
$\alpha_{2\text{-}1}$	0.9206 (0.000)***	0.0083 (0.005)***	0.0092 (0.001)***	0.0462 (0.005)***	0.0436 (0.004)*	0.0311 (0.016)**
β_1	0.0992 (0.000)***	0.9959 (0.001)***	0.9842 (0.012)***	0.9604 (0.010)***	0.9157(0.037)***	0.8966 (0.018)***
$\nu_{\text{-}2}$	-	-	-	-	3.0072(0.002)*	
$\xi_{\text{-}2}$	-	1.0436 (0.0043)**	-	-	-	4.0236 (0.0815)**
Regime-2 μ_2	0.3544 (0.000)***	0.0164 (0.0052)**	0.0186 (0.0128)**	0.0064 (0.0043)*	0.0825 (0.0378)*	0.0164 (0.0078)**

α_2	0.34790 (0.0000)***	0.0067 (0.0019)**	0.0253 (0.0159)**	0.0361 (0.0412)*	0.0752 (0.0471)**	0.0588 (0.0370)**
$\alpha_{2\text{-}2}$	0.6860 (0.000)***	0.0421 (0.0061)***	0.0112 (0.0036)***	0.0325 (0.0065)***	0.0132 (0.0021)**	0.4301 (0.0531)**
β_2	0.8728 (0.000)***	0.9527 (0.131)***	0.9700 (0.0034)***	0.6424 (0.0017)***	0.9138 (0.0071)***	0.9366 (0.0028)***
$\nu_{\text{-}2}$	-	3.8740 (0.8006)**	2.0114 (0.2213)*	-	2.0351 (0.0641)*	-
$\xi_{\text{-}2}$	-	-	-	-	-	-
Regime -3						
μ_3	0.9902 (0.000)***	0.3313 (0.1966)**	0.1103 (0.024)*	11.2219 (2.7450)***	39.3173 (8.7254)***	3.3297 (1.4864)**
α_3	0.0091 (0.0001)***	0.0378 (0.0543)**	4.6579 (2.5728)***	0.9999 (0.000)***	0.0835 (0.0117)***	0.4381 (0.4013)**
$\alpha_{2\text{-}3}$	0.2988 (0.000)***	0.9527 (0.0131)***	0.2188 (1.7872)*	0.0624 (0.0012)***	0.9998 (0.0072)***	0.3463 (7.5013)**
β_3	0.0091 (0.000)***	0.4903 (0.6123)***	0.7803 (0.0079)***	0.0018 (0.000)*	0.000 (0.000)**	0.6535 (0.0058)***
$\nu_{\text{-}3}$	-	1.2856 (0.0485)*	-	-	1.2852 (0.085)*	-
$\xi_{\text{-}3}$	-	-	-	-	-	-
Probabilities						
$P_{1,1}$	0.7342	0.9847	0.9425	0.9364	0.7290	0.7287
$P_{2,1}$	0.6555	0.4096	0.2860	0.9592	0.1148	0.9744
$P_{3,1}$	0.8334	0.6531	0.9582	0.5550	0.9172	0.6105
LL	-821.98	-778.19	-874.02	-802.52	-1000.88	-854.2
AIC	1645.96	1559.38	1752.04	1607.05	2003.76	1712.4
BIC	1655.14	1568.38	1761.63	1616.63	2013.34	1721.98

Moreover, risk management sectors and professional are particularly interested in risk predictions. Based on these considerations, we continue to analyze the results of prediction risk at different horizons and significant levels from two types of models.

4.2 Out-of-Sample Risk Forecasting

The previous hypotheses are addressed in this sub-section. To learn more about risk prediction for the two types of models, large-scale comparison studies are conducted. One-ahead and five-ahead forecasts are used in these comparisons between regime-switching and single-regime scenarios. Each energy commodity market's predicting results include the upside and downside risk, as well as the two quantiles of two distributions. The reason for including so many cases in the empirical process is that these adequate experiments reveal the differences between the two types of models. Indeed, this procedure is used to generate much more precise results and subsequently reach robust conclusions. In fact, the VaR and ES methods are combined to measure the extreme risk of energy commodities in a comprehensive way. Downside risk is considered long position, and upside is short position. Table 3 and 4 provide the one-day predict outcomes for six-types of energy commodities, whereas Table 5 and 6 indicates the five-day predict results. Each table has three benchmark models: GARCH, GJR-GARCH, and TGARCH, each of which include the Regime-Switching (RS) model and the Single-Regime (SR) counterpart with two distributions.
Table 3 and 4 shows that the predicting outcomes for Brent, Petroleum, Gasoline, Heating Oil, Natural Gas, and WTI one-day risk predictions, respectively. When the same distribution is employed, the figures in bold in the table denote the better model between the single-regime

model and the regime-switching equivalent in terms of predicting performance. This kind would be better if it has more bold figures than the other under a basic GARCH-type model, such as GARCH, EGARCH, or TGARCH. In this method, the predicting results are assessed using the bolded figures in the table. Apart from the EGARCH case for Natural gas, the RS model is just superior to the corresponding RS in terms of downside risk under the same distribution for the developed energy commodities. Interestingly, the findings on upside risk outcomes of the gasoline have conversed with the downside. In the case of the emerging oil market, the RS model outperforms the SR model in terms of downside risk, apart from the EGARCH example, however, this conclusion is inconsistent with the upside.

The evidence from the one-day ahead findings just shows that the RS model outperforms the SR model only on the downside, not on the upside. This conclusion is appropriate for both developed and emerging markets. Furthermore, the predicting horizon may have an impact on the result, and a five-day-ahead forecast is made based on this consideration.

To summarise, our findings support the two previously proposed predictions about the risk predicting abilities of the two types of conditional variance models. In terms of energy commodities downside risk predicting, the RS model just outperforms the SR model. The RS models are also appropriate for developing energy commodities. More precisely, risk predicting results represent some important findings. First, the MS-GARCH-types models are suitable for both developed and emerging energy commodities, particularly predicting downside risk. If two types of models are used for the five-day prediction, there are some changes in the risk predictions of the upside risk. Second, our findings require policymakers, risk managers, and investors when hedging and investing in energy commodities, as they must carefully control possible extreme risks. The complex model with regime-switching may not always provide far superiority to, all the time, the SR model in the case of risk predictions for both long and short positions. More importantly, some risk management practitioners and scholars may consider the regime-switching model a preferable option for risk predicting. However, the results obtained based on the regime-switching model can lead to massive losses because this model does not always measure the financial tail risk well, especially for the upside risk in this paper.

Table 3: *One-day forward risk predictions of DQ-test in energy commodities*

DQ test	Brent	Petroleum	Gasoline	Heating oil	Natural gas	WTI
			Long Position-0.01			
Single-Regime GARCH-N	0.672	0.4371	0.6745	0.9572	0.3421	0.4351
EGARCH- N	0.8845	0.5076	0.623	0.7643	0.4576	0.2001
TGARCH- N	0.6713	0.5354	0.4032	0.6872	0.432	0.3982
GARCH-S	0.2152	0.3573	0.3561	0.6461	0.04	0.3065
EGARCH- S	0.5302	0.1765	0.431	0.4701	0.5762	0.371
TGARCH- S	0.3965	0.2301	0.319	0.0231	0.3321	0.3361
MS-GARCH GARCH-EGARCH-TGARCH- N- S	0.0545	0.1298	0.6802	0.1065	0.0365	0.7865
GARCH- EGARCH- N- S	0.1643	0.5587	0.9171	0.1494	0.0294	0.5431
GARCH -TGARCH N- S	0.0476	0.8385	0.7562	0.2542	0.154	0.8142
EGARCH-TGARCH- N- S	0.1457	0.6814	0.8362	0.1376	0.3751	0.6803
EGARCH- N- S	0.1223	0.5467	0.8062	0.046	0.1361	0.745
TGARCH- N- S	0.1098	0.1452	0.9301	0.0636	0.4316	0.7714

			Short position-0.05			
Single-Regime GARCH-N	0.1764	0.3461	0.6262	0.1265	0.0001	0.1782
EGARCH-N	0.4761	0.4087	0.5342	0.134	0.0089	0.2214
TGARCH- N	0.36	0.5371	0.6942	0.1042	0.1563	0.3672
GARCH-S	0.4753	0.4401	0.5643	0.1243	0.1264	0.4583
EGARCH- S	0.4748	0.415	0.6301	0.1561	0.0463	0.5301
TGARCH- S	0.5851	0.5215	0.7164	0.1164	0.084	0.5751
MS-GARCH GARCH-EGARCH-TGARCH- N- S	0.084	0.1165	0.823	0.2367	0.1567	0.6632
GARCH- EGARCH- N- S	0.1315	0.5681	0.8813	0.2224	0.1653	0.6436
GARCH -TGARCH N- S	0.1097	0.8409	0.842	0.3923	0.4303	0.7841
EGARCH-TGARCH- N- S	0.3925	0.8409	0.9217	0.2576	0.0935	0.8024
EGARCH- N- S	0.2517	1	0.8806	0.1604	0.3623	0.6421
TGARCH- N- S	0.32	0.303	0.8325	0.0487	0.138	0.8715

Table 4: *One-day forward risk predictions of CC-test in energy commodities*

CC-test	Brent	Petroleum	Gasoline	Heating oil	Natural gas	WTI
			Long Position-0.01			
Single-Regime GJR-GARCH-N	1783	0.3152	0.1132	0.4214	0.221	0.6571
EGARCH-N	0.4603	0.3105	0.2315	0.3244	0.0431	0.571
TGARCH- N	0.34	0.1004	0.1048	0.3531	0.0935	0.8122
GARCH-S	0.4253	0.419	0.119	0.4413	0.0652	0.6142
EGARCH- S	0.3831	0.3362	0.3362	0.371	0.1043	0.865
TGARCH- S	0.2016	0.3254	0.2431	0.631	0.041	0.5304
MS GARCH						
EGARCH-TGARCH- N- S	0.6705	0.761	0.1115	0.4294	0.221	0.7853
GARCH- EGARCH- N- S	0.5341	0.7112	0.6704	0.5506	0.1425	0.8664
GARCH -TGARCH N- S	0.8506	0.5044	0.3546	0.8403	0.0972	0.8553
EGARCH-TGARCH- N- S	0.6131	0.7532	0.2437	0.8403	0.1612	0.896
EGARCH- N- S	0.7733	1	0.3356	0.1689	0.1047	0.7364
TGARCH- N- S	1	0.5377	0.2422	0.0559	0.224	0.572
			Short position-0.05			
Single-Regime GJR-GARCH-N	0.5661	0.551	0.7631	0.7451	0.0043	0.587
EGARCH-N	0.6631	0.6142	0.3623	0.4632	0.2305	0.3756
TGARCH- N	0.31	0.4852	0.3621	0.5102	0.065	0.767
GJR-GARCH-S	0.4748	0.3421	0.2306	0.6772	0.0004	0.4603
EGARCH- S	0.5661	0.4212	0.0432	0.0421	0.1267	0.655
TGARCH- S	0.776	0.1502	0.139	0.4682	0.0001	0.467
MS-GARCH GARCH-EGARCH-TGARCH- N- S	0.774	0.3371	0.0079	0.7145	0.1087	0.7541
GARCH- EGARCH- N- S	0.5663	0.3998	0.1446	0.5723	0.0465	0.7567
GARCH -TGARCH N- S	0.4746	0.6073	0.105	0.6147	0.108	1
EGARCH-TGARCH- N- S	0.773	0.5903	0.0105	0.8563	0.1123	0.5366

GJR-GARCH- N- S	0.885	0.3912	0.1845	1	0.1268	0.362
TGARCH- N- S	0.6842	0.2467	0.1343	0.5377	0.0132	0.3789

.

Table 5: *five-day forward risk predictions of Dynamic Quantile (DQ)-test in global energy commodities*

DQ-test	Brent	Petroleum	Gasoline	Heating oil	Natural gas	WTI
			Long Position-0.01			
Single-Regime GJR-GARCH-N	0.773	0.0856	0.6261	0.3685	0.0531	0.614
EGARCH-N	1	0.1506	0.5831	0.371	0.0253	0.4731
TGARCH- N	0.615	0.3132	0.3102	0.4631	0.1564	0.5362
GJR-GARCH-S	0.771	0.331	0.5771	0.74	0.0531	0.4001
EGARCH- S	0.788	0.2310	0.3194	0.5525	0.682	0.3134
TGARCH- S	0.3925	0.3135	0.4849	0.3891	0.5412	0.3134
MS-GARCH GARCH-EGARCH-TGARCH-N- S	0.4745	0.7253	0.8384	0.4061	0.3048	0.8254
GARCH- EGARCH- N- S	0.34	0.7468	1	0.311	0.109	0.7856
GARCH -TGARCH N- S	0.6671	0.8734	0.5351	0.2472	0.0362	0.861
EGARCH-TGARCH- N- S	0.5667	0.7887	0.406	0.05	0.0595	0.8662
GJR-GARCH- N- S	0.2361	0.9567	0.6814	0.5632	0.159	0.8988
TGARCH- N- S	0.34	0.8935	0.2943	0.4273	0.5362	0.7411
			Short position-0.05			
Single-Regime GJR-GARCH-N	0.32	0.5661	0.0557	0.3139	0.0045	0.8065
EGARCH-N	0.2041	0.732	0.165	0.7465	0.0288	0.703
TGARCH- N	0.1587	0.661	0.3782	0.3135	0.2766	0.9302
GARCH-S	0.461	0.4741	0.5501	0.3135	0.0119	0.8092
EGARCH- S	0.2351	0.1746	0.1739	0.5131	0.0231	0.7632
TGARCH- S	0.6623	0.5312	0.4428	0.4543	0.0047	0.6134
MS-GARCH GARCH-EGARCH-TGARCH-N- S	0.3925	0.8314	1	0.2174	0.045	0.706
GARCH- EGARCH- N- S	0.2573	0.7319	1	0.3411	0.319	0.9302
GARCH -TGARCH N- S	0.885	0.8664	0.6813	0.6339	0.1202	0.819
EGARCH-TGARCH- N- S	0.663	0.945	0.5362	0.5659	0.0288	0.6213
GJR-GARCH- N- S	0.9262	0.9267	0.6813	0.2308	0.9561	0.8975
TGARCH- N- S	0.3926	0.8127	0.2943	0.2945	0.2108	0.6687

Table 6: *five-day forward risk predictions of Conditional Correlation (CC)-test in global energy commodities*

CC-test	Brent	Petroleum	Gasoline	Heating oil	Natural gas	WTI
			Long Position-0.01			
Single-Regime GARCH-N	0.2413	0.4351	0.2413	0.5361	0.0219	0.7472
EGARCH-N	0.7541	0.8484	0.8384	0.1345	0.0192	0.8365
TGARCH- N	0.6748	0.5959	0.5501	0.7696	0.082	0.7541
GARCH-S	0.671	0.406	0.981	0.5377	0.0687	0.81
EGARCH- S	0.8346	0.3742	0.6851	0.7631	0.1216	0.8501

TGARCH- S	0.7812	0.82	0.5351	0.592	0.001	0.6725
MS-GARCH GARCH-EGARCH-TGARCH-N- S	0.5385	0.5043	0.434	0.5132	0.0425	0.5825
GARCH- EGARCH- N- S	0.6878	0.4293	0.3132	0.7425	0.0712	0.7113
GARCH -TGARCH N- S	0.7886	0.8403	0.5771	0.7631	0.002	0.7603
EGARCH-TGARCH- N- S	0.941	1	0.3493	1	0.0015	0.7718
EGARCH- N- S	0.5806	0.5484	0.0691	1	0.0245	0.9103
TGARCH- N- S	0	1	0.5342	0.5674	0.0166	0.8826
			Short position-0.05			
Single-Regime GARCH-N	0.7523	0.4134	0.1732	0.4601	0.0661	0.7652
EGARCH-N	0.934	0.1954	0.5506	0.1203	0.3134	0.7164
TGARCH- N	0.6531	0.63	0.3235	0.0261	0.0772	0.5972
GARCH-S	0.778	0.1421	0.1686	0.2876	0.0961	0.7261
EGARCH- S	0.6578	0.1833	0.3136	0.0324	0.591	0.7278
TGARCH- S	0.7751	0.1696	0.1686	0.2621	0.0053	0.5315
MS-GARCH GARCH-EGARCH-TGARCH-N- S	0.7412	0.1661	0.5384	0.3402	0.0094	0.6811
GARCH- EGARCH- N- S	0.7415	0.3126	0.6976	0.3914	0.0044	0.1928
GARCH -TGARCH N- S	0.8598	0.0961	0.3135	0.2085	0.0144	0.789
EGARCH-TGARCH- N- S	0.8758	0.5509	0.077	0.3431	0.0054	0.5149
EGARCH- N- S	0.662	0.6813	0.039	0.0187	0.0002	0.6834
TGARCH- N- S	0.7886	0.5362	0.597	0.1543	0.0002	0.5696

These findings on downside risk prediction are consistent with Teterin et al.[32], who demonstrated that the RS model had better prediction accuracy for developed stock markets than the SR model. This conclusion is extended to the commodities market, specifically the developed and emerging energy commodities. However, our conclusions are different from [33,34,35] who indicated that the RS model isn't always better than the SR model. The key reason for this is that our research differs significantly from Zhao et al.[36,37], who did not compare the two types of models under the same distribution**.** Their findings are valid for two specific RS-GARCH models and the three SR-GARCH model instead of the MS-GARCH-type models and their SR counterparts.

5. Conclusion

In this work, we investigate the risk predicting performances between the regime-switching (RS) and single regime (SR) for the global energy commodities. For obtaining robust results, plenty of comprehensive comparisons are implemented, and a related process of comparisons is operated under the same condition. Especially in every energy market, the long and short positions are considered together to see their differences from the downside and upside results. Therefore, empirical results of the in-sample analysis report that the MS model outperforms the SR counterparts in global energy commodity cases. This conclusion that is gained through the risk predictions is suitable for one-day and five-day-ahead cases of energy commodities (Crude oil brent, Petroleum, Gasoline, Heating oil, Natural gas, and Crude oil WTI), some evidence seems interesting in that the upside results are affected by more horizons, but the findings based on the downside risk are stable.

Investors and policymakers who aim to the specific purpose of economic should be vigilant to use the RS model for risk management for long and short positions. Meanwhile, automotive manufactures and energy-intensive global energy commodity prices are directly and indirectly susceptive. They are also carefully making appropriate productions plans when faced with extreme price changes in the future.

Discloser statement

The authors declare no potential conflict of interest.

References

[1] Ahmed, M. Y. and Sarkodie, S. A. (2021). Counterfactual shock in energy commodities affects stock market dynamics: Evidence from the United States. Resources Policy, 72,102-083.

[2] Aloui, C. and Mabrouk, S. (2010). Value-at-risk estimations of energy commodities via long- memory asymmetry and fat-tailed GARCH models. *Energy Policy*, 38(5), 2326–2339.

[3] ELA, 2020. The U.S Energy Facts Explained U.S Energy Information Administration.

[4] Ardia, D. and Hoogerheide, L. F. (2014). GARCH models for daily stock returns: Impact of estimation frequency on Value-at-Risk and Expected Shortfall forecasts. *Economics Letters*, 123(2), 187–190.

[5] Bauwens, L. and Laurent, S. (2005). A new class of multivariate skew densities with application to generalized autoregressive conditional heteroscedasticity models. *Journal of Business and Economic Statistics*, 23(3), 346–354.

[6] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327.

[7] Caporale, G. M. and Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov-Switching GARCH models. *Research in International Business and Finance*, 48, 143–155.

[8] di Sanzo, S. (2018). A Markov switching long memory model of crude oil price return volatility. *Energy Economics*, 74, 351–359.

[8] Dickey, D. A. and Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, 74(366), 427–431.

[9] Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the econometric society*, 987-1007.

[10] Ardia, D. Bluteau, K. Boudt, K. & Catania, L. (2018). Forecasting risk with Markov switching GARCH models: A large-scale performance study. *International Journal of Forecasting*, 34(4),733–747.

[11] Fernández, C. and Steel, M. F. J. (1998). On bayesian modelling of fat tails and skewness. *Journal of the American Statistical Association*, 93(441), 359–371.

[12] Francq, C. and Zakoian, J. M. (2019). GARCH models: structure, statistical inference and financial applications. *John Wiley & Sons*.

[13] Giannopoulos, K. and Tunaru, R. (2005). Coherent risk measures under filtered historical simulation. *Journal of Banking & Finance*, 29(4), 979–996.

[14] Gray, S. F. (1996). Modelling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics*, 42(1), 27–62.

[15] Hamilton, J. D. and Susmel, R. (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics*, 64(1–2), 307–333.

[16] Herrera, A. M. Hu, L. and Pastor, D. (2018). Forecasting crude oil price volatility. *International Journal of Forecasting*, 34(4), 622–635.

[17] Jalal, A. and Rockinger, M. (2008). Predicting tail-related risk measures: The consequences

of using GARCH filters for non-GARCH data. *Journal of Empirical Finance*, 15(5), 868–877.

[18] Jarque, C. M. and Bera, A. K. (1980). Efficient tests for normality, homoscedasticity, and serial independence of regression residuals. *Economics Letters*, 6(3), 255–259.

[19] Klaassen, F. (2002). EMPIRICAL ECONOMICS Improving GARCH volatility forecasts with regime switching GARCH. *Empirical Economics*, 27.

[20] Manigandan, P. Alam, M. S. Alagirisamy, K. Pachiyappan, D. Murshed, M. and Mahmood, H. (2023). Realizing the Sustainable Development Goals through technological innovation: Juxtaposing the economic and environmental effects of financial development and energy use. *Environmental Science and Pollution Research*, 30(3), 8239-8256.

[21] Ljung, G. M., & Box, G. E. P. (1978). On a measure of lack of fit in time series models. *In Biometrika,* 68(2).

[22] Manigandan, P. Alam, S. Alharthi, M. Khan, U. Alagirisamy, K. Pachiyappan, D. and Rehman, A. (2021). Forecasting Natural Gas Production and Consumption in United States-Evidence from SARIMA and SARIMAX Models. *Energies*, 14(19), 6021.

[23] Marimoutou, V. Raggad, B. and Trabelsi, A. (2009). Extreme Value Theory and Value at Risk: Application to oil market. *Energy Economics*, 31(4), 519–530.

[24] Muhammad, N. Aviral, T. Sana, M. and Muhammad, S. (2019). Modelling volatility of precious metals markets by using regime switching GARCH models. 64, 1–8.

[25] Nieto, M. R. and Ruiz, E. (2016). Frontiers in VaR forecasting and backtesting. *International Journal of Forecasting*, 32(2), 475–501.

[26] Sobreira, N. and Louro, R. (2020). Evaluation of volatility models for forecasting Value-at-Risk and Expected Shortfall in the Portuguese stock market. *Finance Research Letters*, 32, 101098.

[27] Tan, C. Y. Koh, Y. B. Ng, K. H. and Ng, K. H. (2021). Dynamic volatility modelling of Bitcoin using time-varying transition probability Markov-switching GARCH model. *North American Journal of Economics and Finance*, 56.

[28] Trottier, D.-A. and Ardia, D. (2015). Moments of Standardized Fernandez-Steel Skewed Distributions: Applications to the Estimation of GARCH-Type Models. *SSRN Electronic Journal*, 1–13.

[29] Saltik, O. Degirmen, S. and Ural, M. (2016). Volatility Modelling in Crude Oil and Natural Gas Prices. *Procedia Economics and Finance*, 38, 476–491.

[30] Nelson DB (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*,59(2), 347–370.

[31] Perron, P. (1990). Testing for a unit root in a time series with a changing mean. *Journal of Business and Economic Statistics*, 8(2), 153–162.

[32] Teterin, P. Brooks, R. and Enders, W. (2016). Smooth volatility shifts and spillovers in U.S. crude oil and corn futures markets. *Journal of Empirical Finance*, 38, 22–36.

[33] World Bank, (2020). A Shock like no other; the impact of COVID-19 on Commodity Market. http://pubdocs.worldbank.org/en/558261587395154178/CMO-April-202 0-Special-Focus-1.pdf.

[34] Duraisamy, P. Alam, MS. Uddin, MA. Kuppusamy, A. Palanisamy, M. (2022). Modelling volatility of petroleum productions by using markov-switching GARCH models. *International Journal of Agricultural Statistical Science*, 18(1):1657-6.

[35] Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control*, 18(5), 931–955.

[36] Zhao, L. T. Zeng, G. R. Wang, W. J. and Zhang, Z. G. (2019). Forecasting oil price using web-based sentiment analysis. *Energies*, 12(22).

[37] Alam, Md. Shabbir. Muntasir, Murshed, Palanisamy, Manigandan. Duraisamy, Pachiyappan. and Shamansurova, Zilola Abduvaxitovna. (2023). Forecasting oil, coal, and natural gas prices in the pre-and post-COVID scenarios: Contextual evidence from India using time series forecasting tools. *Resources Policy,* 81: 103342.