IJEEP

INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY

EJ EconJournals ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2015, 5(4), 979-985.

EJ EconJournals

Markov Regime Switching Generalized Autoregressive Conditional Heteroskedastic Model and Volatility Modeling for Oil Returns

Samet Günay*

Department of Finance, Business School, American University of the Middle East, Kuwait.
*Email: dr.sgunay@gmail.com

ABSTRACT

In conjunction with the recent alternative models, a wide literature has been established for volatility modeling in finance theory. In this study, we examine return volatility of Brent oil returns through generalized autoregressive conditional heteroskedastic (GARCH), exponential GARCH, Glosten-Jagannathan-Runkle GARCH and Markov regime-switching GARCH (MRS-GARCH) models. As a preliminary test concerning the potential regimes, first, we use modified iterative cumulative sum of squares test in order to examine the existence of breaks in the variance of return series. All volatility models are formed under normal, generalized error distribution and Student's t distributions. According to the Akaike information criterion and Bayesian information criterion values, MRS-GARCH model outperforms all other alternative models. Another interesting result is the failure of the models that formed under normal distribution.

Keywords: Markov Regime Switching Generalized Autoregressive Conditional Heteroskedastic, Oil Volatility, Variance Breaks
JEL Classifications: C14, C22, C58, G14

1. INTRODUCTION

Searching the best volatility modeling which fits to stylized facts of financial time series has been one of the most attractive topics of financial econometrics since the 1980s. Following the seminal studies of Engle (1982) and Bollerslev (1986), many alternative volatility models have been introduced that consider different stylized facts. In addition to exponential generalized autoregressive conditional heteroskedastic (EGARCH) and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) models, which take asymmetry effect and unconditional shocks in volatility into account, some long memory models such as integrated GARCH, fractionally integrated GARCH (FIGARCH) and their different versions, adaptive FIGARCH and time-varying FIGARCH, which consider structural breaks and long memory simultaneously, have taken the subject a step further. Besides, regime switching models, first introduced by Hamilton (1989), receive a wide acceptance under the assumption of past states would repeat in future. Dramatic breaks and different states, which arise from economic and political reasons and seem in the behaviors of financial time series, can be caught successfully by regime switching models. Regime switching models can be analyzed under two groups. In the first group, transitions between the regimes occur progressively and can be driven by a specific variable associated with threshold value. Second group can be examined under Markov regime switching (MRS) methodology. In this approximation, discrete transitions are allowed without any specific transition variables. Rather than gradual transitions between the regimes, MRS models consider solid discrete transitions between some unobservable states and assume that these transitions follow an unobserved Markov chain (Markov, 2012). Regime switching processes are defined by multiple discrete regimes each one of which has different dynamics and is characterized by different parameters. While the process in each regime is acknowledged as stationary, in conjunction with the effect of discrete regime switching, total process becomes non-linear stationary (Harris, 1997). As stated by Song (2014), regime switching models and structural break models have different implications. Since structural break models do not accept repeating of past states in next periods, they may not use the information of the data exactly. On the other hand, as stated by Kuan (2002), the second difference arises from the changing types. Whereas the MRS model enables frequent changes at random time points, the structural break models allows just occasion and exogenous changes. Hence, Kuan (2002) suggests using of MRS model for the correlated data. Ang and Timmerman (2011) give three other reasons for the utility of Markov switching model in financial econometrics. First, regime switching is natural and intuitive. Second, MRS model is quite successful in catching of stylized facts seen in financial time series such as fat tails in probability distribution, ARCH effect and time-varying correlations. Last one is the superiority of these models in the consideration of non-linear stylized facts of asset returns.

In this study, volatility of oil returns is analyzed through a bunch of models including MRS-GARCH models. Models used in the empirical section are GARCH, EGARCH and GJR-GARCH and MRS-GARCH models, respectively. As financial time series perform some deviations from normal distribution, we also use Student's t and generalized error distribution (henceforth, GED) besides normal distribution.

2. LITERATURE REVIEW

There is a great deal of interest to MRS models in financial econometrics literature. However, we can see that most of the current literature focuses on the stock, interest and currency market. Generally studies in the literature suggest the superiority of the MRS models. Following the seminal study of Hamilton (1989), many analyses are conducted for different markets by using Markov regimes models. Besides, some modifications are presented and power of the models is improved. For example, Goodwin (1993) uses the MRS model to analyze eight stock markets' business cycles. Filardo (1994) extends the MRS model of Hamilton (1989) and introduce a new model that enables to time varying probabilities of transition between the states. Durland and McCurdy (1994) present another model which allows duration dependent state transitions. They give evidence for the duration dependence of asymmetry and recessions among the non-linearity, recessions and expansions using growth rates of US postwar real gross national product. However, Engel (1994) cannot find evidence concerning superior forecasts of MRS model compared to random walk or forward rates.

In one of the recent studies, Marcucci (2005) demonstrates the robustness of MRS-GARCH model compared to three alternative GARCH models under different distributions through in-sample and out of sample criteria. According to the results, MRS-GARCH model is more credible for the short-term forecasts. However, long-term forecast indicated that the higher performance of GARCH models. Kim et al. (2005) relax the latent state variable controlling regime change is an exogenous assumption and introduces the parsimonious model of endogenous MRS. The authors demonstrate robustness of this model through Monte Carlo Simulations. In a different study, De Jong (2006) examines the nature of power spikes in electricity prices for various markets and states that regime switching models outperform GARCH and Poisson jump models. Marzo and Zagaglia (2010) compare the forecast performance of different volatility models for crude oil futures. While in short term out-of-sample predictability GARCH-GED model outperform other alternatives, according to out-of-sample loss function based on value at risk the most credible model is EGARCH. Alizadeh et al. (2008) use MRS, GARCH, error correction and ordinary least-squares models in order to determine time-varying minimum variance hedge ratio for energy futures. Results of out-of-sample test demonstrate that MRS hedge ratio outperforms other models concerning decreasing of portfolio risk. Janczura and Weron (2011) introduce a new method which enables to lower computational burden by the introduction of independent regimes and give evidence that the model replicates the major stylized facts and fits to the dataset well. Yuan (2011) puts forward an exchange rate forecasting model which outperform random walk in short time horizon by using different sample spans.

Jammazi (2012) states that according to the results of trivariate BEKK Markov-switching GARCH model, there is a high correlation among international recessions and high petrol and stock market volatility periods. Bunnag (2015) shows that oil futures volatility has a significant effect on the carbon emissions futures volatility. Markov (2012) conducts a regime switching Taylor rule prediction in order to examine some potential non-linearity in forward-looking policy reaction function. Rashid and Kocaaslan (2013) state that MRS model has a significant explanatory power for the behavior of GDP volatilities. Eichler and Tuerk (2013) propose a semi-parametric MRS model and empirically prove that when the distribution of the spike process is unknown proposed model may have advantages. Salisu and Fasanya (2012) examine the volatility of West Texas Intermediate oil returns by means of various models and state that in case of not considering the leverage effect spurious result may appear. Billio et al. (2013) improve a new Bayesian multi-chain MRS GARCH model for the dynamic hedging in energy futures. Likewise, Zainudin (2013) shows that when regime switching is taken into account, more successful hedging performance can be obtained. Kritzman et al. (2012) explain how MRS models can be used in the prediction of regimes in market turbulence, inflation and economic growth and obtain a dynamic process that outperforms static asset allocation for the risk-averse investors. Włodarczyk and Zawada (2014) analyze the volatility dynamics of various time series inclusive of MRS model and state that definition of regimes (such as low, moderate and high) and determination of the average duration in each regime provide better hedging in portfolios. Unlike the results of Marcucci (2005), Herrera et al. (2014) demonstrate that the non-switching models provide more credible results in the short term; nevertheless, MRS-GARCH model has slightly higher performance in the long term volatility forecast of oil return volatilities.

3. METHODOLOGY

Using the definition of Kritzman et al. (2012) MRS process can be presented as below: Probability of being in regime i can be explained as follows:

$$\Pr(X_1 = i) = p_i \tag{1}$$

Where, X_1 is the first regime in Markov chain. Let's show the transition probability matrix between regimes Γ. γ_{ij} parameters in this matris denote the transition probabilities from regime i to regime j.

$$\Gamma = \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix} \quad (2)$$

And

$$\gamma_{ij} = \Pr(X_t = j | X_{t-1} = i) \quad (3)$$

Where, t denotes the time. Therefore, Markov chain will be either in regime $X_t = 1$ or $X_t = 2$ in time. Each regime produces Y_t observations in accord with the distribution π_i. For a discrete distribution π_i can be explained as follows:

$$\pi_i = \Pr(Y_t = s | X_t = i) \quad (4)$$

Demonstrates that the current regime, X_t, dictates the probability that Y_t will have a specific value s.

A standard k - state MRS model can be written as follows,

$$Y_t = \mu(s_t) + \sigma(s_t)\varepsilon_t, \varepsilon_t \sim N(0,1) \quad (5)$$

Such that

$$\begin{Bmatrix} Y_t = \mu_1 + \sigma_1\varepsilon_t, & if s_t = 1 \\ Y_t = \mu_2 + \sigma_2\varepsilon_t, & if s_t = 2 \\ \cdots & \cdots \\ Y_t = \mu_k + \sigma_k\varepsilon_t, & if s_t = k \end{Bmatrix} \quad (6)$$

Interpretation of the model depends on value k. For instance, if there are two states governing the process there will be two different s values. When $s_t = 1$ may become downward trend period being related to negative mean change, $s_t = 2$ is a upward trend period with positive mean change. In the case of three states, one of the states may become trendless period and in which it fluctuates around a mean zero (Yuan, 2011).

MRS-GARCH model consists of four elements: Conditional mean, conditional variance, regime process and conditional distribution. Conditional mean process, which is mostly modeled through random walk, can be presented as follows:

$$r_t = \mu_t^{(i)} + \varepsilon_t = \delta^{(i)} + \varepsilon_t \quad (7)$$

Where, $i = 1, 2$, $\varepsilon_t = \eta_t \sqrt{h_t}$ and η_t are zero mean and unit variance processes. For GARCH (1.1) conditional variance of r_t can be written as below:

$$h_t^{(i)} = \alpha_0^{(i)} + \alpha_1^{(i)}\varepsilon_{t-1}^2 + \beta_1^{(i)} h_{t-1} \quad (8)$$

Where, h_{t-1} is a state-independent mean of past conditional variance (Marcucci, 2005).

4. EMPIRICAL FINDINGS

4.1. Data Analysis

In this study, return volatility of Brent oil prices is analyzed under different models during the period of December 1, 1998 and January 30, 15. The oil price data is obtained via the database of St. Louis Fed. Empirical tests are conducted with GARCH, EGARCH, GJR-GARCH and MRS-GARCH models using Matlab and Gauss software's. In spite of the fact that there is a wide literature concerning return volatility modeling of oil prices, most of these studies do not consider regime switching properties. As stated in Section 2, whereas MRS-GARCH model can fit data better than other alternative models. Because the period we analyzed has some political and economic issues, which may create different states in the volatilities, MRS-GARCH model potentially can be a better option in modeling of volatility. Modified iterative cumulative sum of squares (ICSS) test also gives some predictions concerning the existence of breaks and regimes in volatility. Figure 1 presents returns of the Brent oil prices in the period of December 1, 1998 and January 30, 15. As shown in Figure 1, there is a significant turbulence in returns of oil prices in November 2001 and between September 2008 and May 2009.

In this section, in order to see the effect of the turbulences on volatility, we analyze possible breaks in the volatility of oil returns. Structural break analysis in return volatility is conducted through modified ICSS test by Sanso et al. (2004). Deviation from the normal distribution is a common stylized fact of financial time series. Considering this fact Sanso et al. (2004) propose a modified ICSS test and give evidences concerning the spurious results of ICSS test of Inclán and Tiao (1994). Modified ICSS test provides credible results for leptokurtic and conditionally heteroskedastic time series. The authors develop two test statistics for that reason: Kappa 1 (κ_1) and Kappa 2 (κ_2). While the first test (κ_1) takes daviations from the normal distribution into account, it is based on the independence of the sequence random variables assumption as in classical ICSS test. The second test (κ_2) consider both deviations from normal distribution and conditional heteroscedasticity.

According to the results of modified ICSS test in Table 1, there is one break for the κ_1 test and are two breaks for the κ_2 test in the volatility of oil returns. For the κ_2 test break dates are May 25, 2004 and October 13, 2005. Two breaks means three different regimes. However, as we aforementioned before there are essential differences between structural break and regime switching analysis. Hence, obtained break/regime information will be used as a proxy for the rest of the analysis. Under the possibility of different regimes, first we analyze uniregime models (GARCH, EGARCH, GJR-GARCH) and second we use MRS-GARCH model to take regime switching into account.

4.2. Volatility Modeling

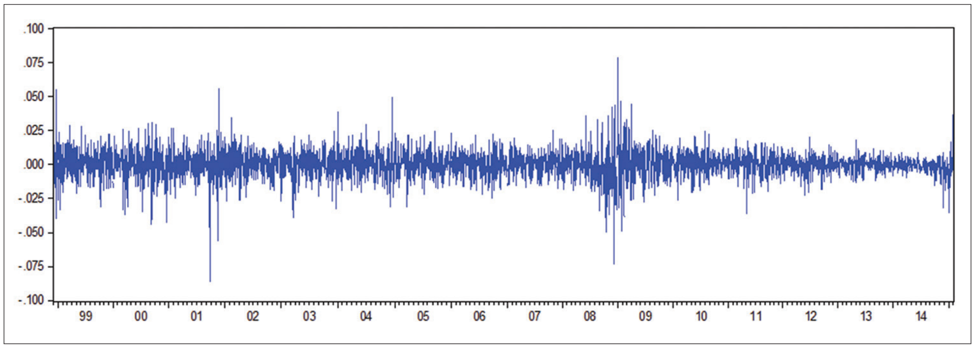
In the modeling of volatility, first we use GARCH model. As financial time series has deviations from normal distribution, in conjunction with the normal distribution, we also use Student's

Table 1: Modified ICSS test results

Findings	κ_1 test	κ_2 test
Number of observations	1756	1396 and 1756
Break dates	October 13, 2005	May 25, 2004 and October 13, 2005

ICSS: Iterative cumulative sum of squares, κ_1: Kappa 1, κ_2: Kappa 2

Figure 1: Brent crude oil returns



t and GED in the modeling of volatility. Results of GARCH model are presented in Table 2. Asymptotic standard errors are presented within parentheses and t statistics are within square brackets. As seen from the alpha and beta parameters obtained for mean and variance, the sum of these values is close to unity. This finding means that there is high persistency for volatility under all type of distributions. On the other hand, both and alpha parameters are statistically significant at 95% confidence level. Significant tail statistic (υ) of Student's t distribution confirm the fatness of the tail differently from normal distribution. Likewise, tail statistic of GED also is statistically significant. Finally, as model selection criteria, log-likelihood values of models show that highest log-likelihood value belongs to Student's t distribution. According to this implication, GARCH-t model outperforms other alternative models.

As a second model, we use EGARCH model of Nelson (1991). Nelson (1991) claims that the existence of three drawbacks in standard GARCH model and introduces EGARCH model as an alternative. These drawbacks can be presented as follows: Ignoring the negative correlation between current return and future return, parameter restrictions and difficulties in commenting of shocks on conditional variance. EGARCH model has an additional leverage term (ξ) and so can catch the asymmetry in volatility clustering. Thus changes in volatility arising from good and bad news can be incorporated in the model. As can be seen from the Table 3, leverage parameter ξ is statistically significant and has a negative sign.

This finding means that negative and positive shocks on volatility have different effects. Leverage parameter is statistically significant in all alternative models. Tail parameter of GED and Student's t distribution is significant, as well. This finding also coincides with the fat tail property of financial time series. According to log-likelihood value, the best fitting EGARCH model for the oil data is obtained under GED among the alternative distributions.

Next model analyzed is GJR-GARCH that takes into account the effect of unconditional shocks on volatility with an additional term. Volatility persistency in the model strictly depends on the preferred distribution type. For the existence of leverage effect, parameter ξ should have larger values than zero. As seen from the results in Table 4, similar to the outputs of GARCH model, the most successful findings are obtained under Student's t distribution. All of the parameters of GJR-GARCH-t model are

Table 2: GARCH (1.1) results

Parameters	GARCH-N	GARCH-t	GARCH-GED
δ	0.05036	0.0661	0.0665
	(0.0278)	(0.0271)	(0.0263)
	[1.8087]	[2.4400]	[2.5212]
α_0	0.0555	0.0531	0.0552
	(0.0085)	(0.0104)	(0.0114)
	[6.4906]	[5.0870]	[4.8384]
α_1	0.0699	0.0598	0.0647
	(0.0046)	(0.0075)	(0.0077)
	[15.1896]	[7.9314]	[8.4055]
β_1	0.9172	0.9264	0.9215
	(0.0052)	(0.0077)	(0.0081)
	[174.7140]	[119.0511]	[113.2445]
υ	-	7.5383	1.4013
		(0.7694)	(0.0365)
		[9.7967]	[38.3058]
Log (L)	−8494.6432	−8424.8912	−8432.7557

* and ** indicates the 95% and 99% confidence level, respectively Asymptotic standard errors are presented within () and t statistics are within []. GARCH: Generalized autoregressive conditional heteroskedastic, GED: Generalized error distribution

Table 3: EGARCH (1.1) results

Parameter	EGARCH-N	EGARCH-t	EGARCH-GED
δ	−0.0039	0.0332	0.0353
	(0.0290)	(0.0276)	(0.0269)
	[−0.1345]	[1.2047]	[1.3120]
α_0	−0.0775	−0.0654	−0.0711
	(0.0065)	(0.0101)	(0.0103)
	[−11.8477]	[−6.4342]	[−6.9021]
α_1	0.106508	0.082498	0.091515
	(0.007450)	(0.011448)	(0.011907)
	[14.29707]	[7.206154]	[7.685682]
β_1	0.993909	0.995904	0.995281
	(0.001425)	(0.001626)	(0.001788)
	[697.3606]	[612.4244]	[556.6922]
ξ	−0.037142	−0.030576	−0.032935
	(0.004086)	(0.005903)	(0.005858)
	[−9.090641]	[−5.179933]	[−5.622003]
υ	-	7.6042	1.4171
		(0.7871)	(0.0362)
		[9.6605]	[39,0826]
Log (L)	−8483.1923	−8424.8912	−8422.3791

* and ** indicates the 95% and 99% confidence level, respectively Asymptotic standard errors are presented within () and t statistics are within []. EGARCH: Exponential generalized autoregressive conditional heteroskedastic, GED: Generalized error distribution

Table 4: GJR-GARCH (1.1) results

Parameter	GJR-GARCH-N	GJR-GARCH-t	GJR-GARCH-GED
δ	0.0349	0.0619	0.0608
	(0.0288)	(0.0273)	(0.0267)
	[1.2149]	[2.2653]	[0.0373]
α_0	0.0567	0.0506	0.0536
	(0.0083)	(0.0098)	(0.0108)
	[6.7664]	[5.1612]	[4.9462]
α_1	0.0928	0.0769	0.0836
	(0.0057)	(0.0090)	(0.0091)
	[16.1426]	[8.4585]	[9.1256]
β_1	0.91998	0.9298	0.9249
	(0.0051)	(0.0075)	(0.0078)
	[177.8035]	[123.2307]	[117.8634]
ξ	0.0402	0.0356	0.0383
	(0.0062)	(0.0095)	(0.0096)
	[6.4376]	[3.7498]	[3.9858]
υ	-	7.8157	1.4155
		(0.8177)	(0.0373)
		[9.5574]	[37.9300]
Log (L)	−8483.36301	−8418.2479	−8425.7543

* and ** indicates the 95% and 99% confidence level, respectively
Asymptotic standard errors are presented within () and t statistics are within [].
GJR-GARCH: Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroskedastic, GED: Generalized error distribution

statistically significant and asymmetry parameter ξ of the model has a positive sign in accordance with our expectations. Besides, tail parameter of the distributions is also statistically significant.

Final model used in the empirical analysis is the MRS-GARCH model. As it can be seen from the results in Table 5, while the constant values for conditional mean and variance are statistically significant for the first regime, for the second regime, all constant values are not significant under the alternative four distributions. Parameter α_0^i, which gives information for the long term behavior of volatility, demonstrates different characteristics under two regimes. Whereas both two conditional mean parameters in normal distribution are not statistically significant, all other ARCH and GARCH parameters are statistically significant under GED, Student's t, skewed Student's t (t2) distributions. As stated before, deviations from the normal distribution point out fat tails in return distributions. Besides, both ARCH and GARCH parameters in the first and second regimes indicate different behaviors. While the first regime shows high volatility and high persistency in volatility, both these two properties are quite low in the second regime.

Furthermore, transition probabilities of all regimes are statistically significant and require the rejection of null hypothesis. Transition probabilities are very close to unity under all alternative distributions meaning that all regimes show persistency. According to log-likelihood statistic, the best fitting distribution for the data is skewed-t (t2) distribution. Tail and asymmetry parameters of the distribution are all statistically significant. In Table 6, we compare the all of the alternative model and distributions through the log-likelihood, Akaike information criterion (AIC) and Bayesian information criterion (BIC) criteria's and sort for the ranking. As can be seen MRS-GARCH model, outperform all alternative models for the aforementioned criteria's.

Table 5: MRS-GARCH (1.1) results

Parameter	MRS-GARCH-N	MRS-GARCH-t2	MRS-GARCH-t	MRS-GARCH-GED
δ^1	−0.8137	0.1714	0.1715	0.1717
	(0.1658)	(0.0456)	(0.0456)	(0.0459)
	[−4.9081]	[3.7596]	[3.7568]	[3.7424]
δ^2	0.0827	−0.0070	−0.0056	0.0146
	(0.0284)	(0.0375)	(0.0374)	(0.0359)
	[2.9113]	[−0.1874]	[−0.1509]	[0.4064]
α_0^1	1.2928	0.3511	0.3554	0.3984
	(0.2208)	(0.1061)	(0.1068)	(0.1194)
	[5.8547]	[3.3099]	[3.3296]	[3.3365]
α_0^2	0.0048	0.0102	0.0101	0.0097
	(0.0112)	(0.0067)	(0.0065)	(0.0064)
	[0.4279]	[1.5179]	[1.5485]	[1.5259]
α_1^1	0.0146	0.0582	0.0585	0.0702
	(0.0148)	(0.0138)	(0.0138)	(0.0140)
	[0.9817]	[4.2104]	[4.2454]	[5.0128]
α_1^2	0.0011	0.0452	0.0449	0.0459
	(0.0085)	(0.0109)	(0.0108)	(0.0108)
	[0.1341]	[4.1307]	[4.1741]	[4.2569]
β_1^1	0.9804	0.8731	0.8726	0.8561
	(0.0338)	(0.0281)	(0.0280)	(0.0310)
	[29.0112]	[31.0362]	[31.1680]	[27.6330]
β_1^2	0.9528	0.9529	0.9530	0.9524
	(0.0072)	(0.0109)	(0.0108)	(0.0108)
	[132.3364]	[87.2940]	[88.4659]	[88.2416]
p	0.7479	0.9997	0.9997	0.9998
	(0.0426)	(0.0003)	(0.0003)	(0.0003)
	[17.5692]	[2988.7951]	[3186.1492]	[3507.6919]
q	0.9701	0.9995	0.9996	0.9996
	(0.0060)	(0.0006)	(0.0006)	(0.0005)
	[161.762]	[1584.6224]	[1678.0620]	[1866.3877]
υ_1	-	7.7851	7.5729	1.4253
		(1.0889)	(0.8185)	(0.0389)
		[7.1489]	[9.25130772]	[36.552323]
υ_2	-	7.2828	-	-
		(1.2316)		
		[5.9131]		
Log (L)	−8440.5715	−8399.3431	−8399.3858	−8407.7836

* and ** indicates the 95% and 99% confidence level, respectively Asymptotic standard errors are presented within () and t statistics are within []. MRS-GARCH: Markov regime-switching generalized autoregressive conditional heteroskedastic,
GED: Generalized error distribution

According to AIC and BIC criteria, MRS-GARCH-t model seem as the most successful model among the alternatives. As for second and third models, they are other fat tail distribution models: MRS-GARCH-t2 and MRS-GARCH-GED. In accordance with our theoretical expectations, models, which were formed with normal distribution, share the last four ranks in the performance list. If we leave the distribution type out of assessment, we can say that while the MRS-GARCH model explicitly outperforms other alternatives, there is no straight implication for the performance order of other models.

5. CONCLUSION

Using three alternative models (GARCH, EGARCH, GJR-GARCH), we compare the performance of MRS-GARCH

Table 6: Comparison of alternative models

Parameter	k	log (L)	Rank	AIC	Rank	BIC	Rank
GARCH-N	4	−8494	13	4.149728	13	4.151303	13
GARCH-t	5	−8424	6	4.116158	6	4.118126	6
GARCH-GED	5	−8432	9	4.119998	9	4.121966	9
EGARCH-N	5	−8483	11	4.144625	11	4.146593	11
EGARCH-t	6	−8424	7	4.116646	7	4.119008	7
EGARCH-GED	6	−8422	5	4.115419	5	4.117781	5
GJR-GARCH-N	5	−8483	12	4.144709	12	4.146677	12
GJR-GARCH-t	6	−8418	4	4.113402	4	4.115764	4
GJR-GARCH-GED	6	−8425	8	4.117068	8	4.119429	8
MRS-GARCH-N	10	−8440	10	4.126256	10	4.130192	10
MRS-GARCH-t2	12	−8399	1	4.107101	2	4.111825	2
MRS-GARCH-t	11	−8399	2	4.106634	1	4.110964	1
MRS-GARCH-GED	11	−8407	3	4.110734	3	4.115064	3

GARCH: Generalized autoregressive conditional heteroskedastic, EGARCH: Exponential generalized autoregressive conditional heteroskedastic, GJR-GARCH: Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroskedastic, MRS-GARCH: Markov regime-switching generalized autoregressive conditional heteroskedastic, GED: Generalized error distribution, AIC: Akaike information criterion, BIC: Bayesian information criterion

model for the Brent oil return volatilities. Because of the mostly seemed fat tails in the return distributions of financial time series, all models we analyze are performed under GED and Student's t distribution in conjunction with normal distribution. According to the results obtained from modified ICSS test, for κ_1 and κ_2 there are one and two breaks in the volatility of Brent oil returns. As these findings may become a sign of the existence of different regimes in the volatility, apart from GARCH, EGARCH, GJR-GARCH, we also use MRS-GARCH model in empirical analysis. AIC and BIC results indicate that the best fitting model to data is MRS-GARCH. In the performance rating based on the distribution type, the most failure results are attained under normal distribution.

In conclusion we see that among the thirteen models, MRS-GARCH-t outperforms other alternatives. As widely accepted in finance literature, models which do not take into account the stylized facts of financial time series may cause artificial findings in empirical analysis. In this study, it is once again revealed that accurate return distribution has a significant effect over the results. Another important contribution, as in return distribution type, regime switching properties of the volatility is also a critical feature to be considered. These facts can be regarded as a useful knowledge in the determination of accurate volatility models in risk management.

REFERENCES

Alizadeh, A.H., Nomikos, N.K., Pouliasis, P.K. (2008), A Markov regime switching approach for hedging energy commodities. Journal of Banking and Finance, 32, 1970-1983.

Ang, A., Timmerman, A. (2011), Regime Changes and Financial Markets, CEPR Working Paper.

Billio, M., Casarin, R., Osuntuyi, A. (2013), Markov Switching GARCH models for Bayesian Hedging on Energy Futures Markets, Syrto Working Paper Series, Working Paper No. 12. p1-29.

Bollerslev, T. (1986), Generalized autorregressive conditional heteroskedasticity. Journal of Econometrics, 31, 307-327.

Bunnag, T. (2015), Volatility transmission in oil futures markets and carbon emissions futures. International Journal of Energy Economics and Policy, 5(3), 647-659.

De Jong, C. (2006), The nature of power spikes: A regime-switch approach. Studies in Nonlinear Dynamics & Econometrics, 10(3), 1-26.

Durland, J.M., McCurdy, T.H. (1994), Duration dependent transitions in a Markov model of U.S. GNP growth. Journal of Business and Economic Statistics, 12, 279-288.

Eichler, M., Tuerk, D. (2013), Fitting semiparametric Markov regimeswitching models to electricity spot prices. Energy Economics, 36, 614-624.

Engel, C. (1994), Can the Markov switching model forecast exchange rates. Journal of International Economics, 36, 151-165.

Engle, R. (1982), Autorregressive conditional heteroskedasticity with estimates of United Kingdom inflation. Econometrica, 50, 987-1008.

Filardo, A.J. (1994), Business cycle phases and their transitional dynamics. Journal of Business and Economic Statistics, 12, 299-308.

Goodwin, T.H. (1993), Business cycle analysis with a Markov switching model. Journal of Business and Economic Statistics, 11, 331-339.

Hamilton, J.D. (1989), A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica, 57, 357-384.

Harris, G.R. (1997), Regime switching vector autoregressions: A Bayesian Markov Chain Monte Carlo approach. Proceedings of the 7th International AFIR Colloquium, 1, 421-450.

Herrera, A.M., Hu, L., Pastor, D. (2014), Forecasting crude oil price volatility. Available from: http://www.econ.wayne.edu/agoodman/placement/Pastor/ForecastingCrudeOilPriceVolatility.pdf.

Inclán, C., Tiao, G. (1994), Use of the cumulative sums of squares for retrospective detection of changes of variance. Journal of the American Statistical Association, 89, 913-923.

Jammazi, R. (2012), Oil shock transmission to stock market returns: Wavelet-multivariate Markov switching GARCH approach. Energy, 37, 430-454.

Janczura, J., Weron, R. (2011), Efficient estimation of Markov regime-switching models: An application to electricity spot prices, HSC Research Reports HSC/11/02, Hugo Steinhaus Center, Wroclaw University of Technology.

Kim, C.J., Piger, J.M., Startz, R. (2005), Estimation of Markov Regime-Switching Regression Models with Endogenous Switching, Federal Reserve Bank of St. Louis: Working Paper 2003-015C.

Kritzman, M., Page, S., Turkington, D. (2012), Regime shifts: Implications for dynamic strategies. Financial Analysts Journal, 68(3), 22-39.

Kuan, C.M. (2002), Lecture on the Markov switching. Institute of Economics Academia Sinica. Available from: http://www.idv.sinica.edu.tw/ckuan/pdf/lecmarkn.pdf.

Marcucci, J. (2005), Forecasting stock market volatility with regime-switching GARCH models. Studies in Nonlinear Dynamics and Econometrics, 9, 1-53.

Markov, N. (2012), A Regime Switching Model for the European Central Bank, Working Paper Series, WPS 10091, Universite de Geneve.

Marzo, M., Zagaglia, P. (2010), Volatility forecasting for crude oil futures. Applied Economics Letters, 17(16), 1587-1599.

Nelson, D.B. (1991), Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59, 347-370.

Rashid, A., Kocaaslan, O.K. (2013), Does energy consumption volatility affect real GDP volatility? An empirical analysis for the UK. International Journal of Energy Economics and Policy, 3(4), 384-394.

Salisu, A.A., Fasanya, I.O. (2012), Comparative performance of volatility models for oil price. International Journal of Energy Economics and Policy, 2(3), 167-183.

Sanso, A., Arragoo, V., Carrion, J.L. (2004), Testing for change in the unconditional variance of financial time series. Revistade Economi´a Financiera, 4, 32-53.

Song, Y. (2014), Modelling regime switching and structural breaks with an infinite hidden Markov model. Journal of Applied Econometrics, 29(5), 825-842.

Włodarczyk, A., Zawada, M. (2014), Evaluation of Volatility of Clean Energy Stock Prices in a Regime-Switching Environment, The 8th International Days of Statistics and Economics, Prague. p1664-1675.

Yuan, C. (2011), Forecasting exchange rates: The multi-state Markov-switching model with smoothing. International Review of Economics & Finance, 20(2), 342-362.

Zainudin, R. (2013), The effect of regime shift in minimum variance hedging ratio: The evidence of the crude palm oil market. Investment Management and Financial Innovations, 10(4), 189-198.