The Study of the Long Memory in Volatility of Renewable Energy Exchange-Traded Funds (ETFs)

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***Abstract*—This research applied original price return and adjustment price return for both renewable and unrenewable energy ETFs. Comparing the long memory in volatility and asymmetric volatility of renewable and unrenewable energy ETFs, this study used three models, fractional autoregressive integrated moving average (ARFIMA), a combination of ARFIMA and fractionally integrated exponentially generalized autoregressive conditional heteroscedasticity (ARFIMA-FIEGARCH) and ARFIMA with hyperbolic generalized autoregressive conditional heteroscedasticity (ARFIMA-HYGARCH) models. The results show that by using the adjustment price return data samples, then the results are similar with original price return ETFs. Both unrenewable and renewable energy ETFs have a long memory in volatility and negative asymmetric volatility. ARFIMA-FIEGARCH model perform better to investigate long memory in volatility and asymmetric volatility for both energy ETFs among others.**

***Index Terms*—Long memory in volatility, asymmetric volatility, renewable energy ETFs.**

I. Introduction

Renewable energy is commonly defined as energy that comes from resources which are naturally refilled on a human life, for example, like sunlight, rain, hydro power, biofuels, waves, wind and geothermal power. The International Energy Outlook 2013 predicted that world consumption of energy will rise by 56% in 2040. Renewable energy and nuclear power are the world's fastest-growing energy sources, each increasing by 2.5% per year. In addition, fossil fuels continue to supply almost 80% of world energy in 2040. Prediction shows that unrenewable energy such as fossil fuels and liquid fuels (petroleum) remain the biggest source of energy. The liquids share of world energy consumption decreases from 34 % in 2010 to 28% in 2040. As predicted high oil prices made people seeking for other resources. According to U.S Energy Information Administration research about the renewable share of total energy use rises from 11% in 2010 to 15% in 2040 and the nuclear share grows from 5 % to 7 %.

In 1993, State Street Global Advisors was launched for the first time, Exchange-traded fund (ETF) has grown significantly since that period. Even though volatility and correlations in ETFs have increased over the past few years, however, these conditions always challenge investors to get profit from investing ETFs. That's the reason why the risks have caused markets to function in a different way. In particular, correlation risk with ETFs has connected the large fluctuations in volatility and enhanced in the equity market. Mazza (2012) revealed that a good advantage of investing in ETFs that displayed correlations and higher volatility [1].

There are two motivations of this study. First, this work examines and compares original and adjustment price ETFs in order to find long memory and the asymmetric volatility in renewable and unrenewable energy ETFs. Next is to reveal the best model among ARFIMA, ARFIMA-FIEGARCH and ARFIMA-HYGARCH models to find long memory and the asymmetric volatility.

The contribution of this study revealed that the adjustment price return for ETFs similar is with the original price return. Furthermore, this paper found that there are long memory and the asymmetric volatility of renewable and unrenewable energy ETFs. Finally, this study also revealed that ARFIMA-FIEGARCH is the best model to explain long memory and the asymmetric volatility, among others.

This article is organized in five sections. Section II presents the literature review. Section III describes the data and explains ARFIMA, ARFIMA-FIEGARCH and ARFIMA-HYGARCH models. Section IV presents the empirical results of the ETF for long memory and asymmetric volatility of renewable and unrenewable energy ETFs, and Section V provides the conclusion.

II. Literature Review

Nowadays, many people and nations concern with clean energy/renewable energy, because their release for unrenewable energy decreasing from year to year. In the United States 15.9 gigawatts of installed sunlight power provided the power enough to supply above 3.2 million American households. The Department Energy of United States in 2014 declared over $53 million for 40 innovative research and development projects that have a purpose to cut down the cost of solar energy[1].

Schoenfeld mentioned that ETFs can be one or a combination of investment [2]. The global investment market has witnessed a sudden increase in the number and capitalization of ETFs. Gao explained that the reasons for this expansion were diversification, convenience, simplicity, cost-effectiveness, transparency, flexibility, tax-efficiency, and variety [3]. ETFs have certainly caught investors' attention on the many available investment opportunities that surfaced from their home markets.

Many economists and researcher pay more attention about the models to examine long memory in time series data. The example of ARFIMA model studied by Granger; Granger

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[1] http://energy.gov/articles/energy-department.

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and Joyeux; Hosking etc. [4]-[6]. Actually, Engle is the first to propose an ARCH model of conditional volatility [7]. Thus, expanding with many models, GARCH model created by Bollerslev, the IGARCH develop by Engle and Bollerslev, and the FIGARCH model proposed by Baillie *et al*. [8]-[10]. Moreover, FIEGARCH model proposed by Bollerslev and Mikkelsen [11]. More recently, Davidson was proposed HYGARCH model, and argued that original long memory compared with FIGARCH model was more flexible than IGARCH and FIGARCH models [12].

Gutierrez *et al*. found different return and volatility of Asian ETFs which traded in the United States [13]. Liu *et al*. forecasted volatility and value at risk SPDRs with GARCH, IGARCH, EGARCH models [14]. They found that EGARCH model revealed asymmetric volatility, thus IGARCH/EGARCH can used for shorter/longer trading period. Moreover, GARCH model may over-predict volatility, providing adequate value at risk forecast. By using ARFIMA-FIGARCH models, Chen and Diaz found that no significant long memory process can be found between Green ETFs [15]. Ruiz and Viega used A new stochastic volatility model (A-LMSV) and FIEGARCH models and found leverage effect and long memory in volatility of the daily return of the Standard & Poor 500 S&P 500 and Deutscher Aktien IndeX (DAX) indexes [16]. Tang and Shieh revealed that HYGARCH model was outperformed for investigate the long memory for the S&P 500, Nasdag 100 and futures prices [17].

Even though many research studies about long memory, forecasting and asymmetric volatility ETFs, however, no specific research concern the long memory properties with renewable and unrenewable energy ETFs. Moreover, this study tends to prove that there is have any difference between ARFIMA, ARFIMA-FIEGARCH, and ARFIMA-HYGARCH models to reveal long memory exist in renewable and unrenewable energy ETFs.

III. Data and Methodology

This research uses three daily closing prices and adjustment of unrenewable energy ETFs and two renewable energy ETFs data. Sources from Yahoo Finance with different inception date up to 13 November 2014. For unrenewable energy used natural gas, coal and oil, and for renewable ETFs used solar and clean energy ETFs. This study uses ARFIMA, ARFIMA-FIEGARCH and ARFIMA-HYGARCH models.

A. Autoregressive Fractionally Integrated Moving Average (ARFIMA)

The ARFIMA model proposed by Granger and Joyeux allows the parameter d to be the non-integer or fraction. If there is 0<*d*<0.5, it will represent the time series with long memory effect [5]. The mathematical model ARFIMA (p, d, q) is defined as below:

$$\Phi(L)(1-L)^d(y_t-\mu_t)=\Psi(L)\varepsilon_t\ , \qquad (1)$$

where *d* represent the fractional integration, real number parameter, *L* is the lag operator, and ε_t is a noise residual.

$\Phi(L)=1-\Phi_1L-\cdots-\Phi_pL^p=1-\sum_{j=1}^{p}\Phi_jL^j$ are the polynomials in the lag operator of order *p*, $\Psi(L)=1+\sum_{j=1}^{p}\Psi_jL^j$ are the polynomials in the lag operator of order q where both p and q are integer. ε_t is a Gaussian white noise with variance 1, and μ_t is y_t's mean.

The fractional differencing lag operator $(1-L)^d$ can be further illustrated by using the expanded equation below:

$$(1-L)^d=1-dL+\frac{d(d-1)}{2!}L^2-\frac{d(d-1)(d-2)}{3!}L^3+.. \qquad (2)$$

Based on Paul *et al*., when *d* = 0, then the variable has short memory and the effect of shocks to ε_t decays faster (geometric decay) [18]. When *-0.5 <d<0.5*, the variable is stationary, wherein the effect of market shocks to ε_t decays at a gradual rate to zero (hyperbolic decay). When *d = 1*, there is the presence of a unit root process.

Furthermore, Hsieh and Lin showed that there is an intermediate memory when *-0.5<d<0*, representing that the autocorrelation function decays slower [19]. There is a short memory when *d*=0, the Autocorrelation function decays faster. If there is 0<*d*<0.5, it represents the time series with long memory effect. The time series variable is non-stationary when *d≥0.5*, at the same time as the time series variable is stationary when *d≤0.5*.

B. ARFIMA-Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroskedasticity (ARFIMA-FIEGARCH)

The FIEGARCH model was proposed by Bollerslev and Mikkelsen as followings [10]:

$$\Phi(L)(1-L)^d(\log\sigma_t^2-\omega)=\Psi(L)g(z_t-1)\ , \qquad (3)$$

where ω is the mean of the logarithmic conditional variance $\Phi(L)$ and $\Psi(L)$ are polynomials in lag operator $\Phi(L)=1-\Phi_1L-\cdots-\Phi_pL^p=1-\sum_{j=1}^{p}\Phi_jL^j$; $\Psi(L)=1+\sum_{j=1}^{p}\Psi_jL^j$. $(1-L)^d$ is the fractional difference operator, where *d* is the order of fractional integration in log variance. When 0<*d*<1 allows for stronger volatility persistence than that GARCH by $\Phi(L)$ and $\Psi(L)$ Christensen *et al*., [20]. Nelson mentions that there is short memory when *d*=0 [21]. In FIEGARCH model, when $|\Phi|<1$ and $|d|<0.5$ is stationary proposes by Zaffaroni [22]. The exponential or asymmetry feature explains by $\log\sigma_t^2.\,g(z_t)=\theta z_t+\gamma(|z_t|-E|z_t|)$, where $z_t={\varepsilon_t}/{\sigma_t}$ is the normalized innovation and $\gamma\varepsilon_t$ is news impact function and ε_t is a Gaussian white noise with variance 1. Thus, γ is parameter to measure the leverage effect, *d* is a long memory parameter. θ explains an asymmetry in news impact on volatility. When θ<0 means that negative innovations induce higher volatility than positive innovations Christensen *et al*. [20].

C. ARFIMA-Hyperbolic Generalized Autoregressive Conditional Heteroskedasticity (ARFIMA-HYGARCH)

Unexpected behavior of the FIGARCH model, perhaps due to any inherent paradoxes less than to the fact that the unit-amplitude restriction has been transplanted into a model of volatility. In contrast with FIGARCH model, HYGARCH allows combining the desired properties of hyperbolically decaying impulse response coefficients and covariance stationary Ruiz and Veiga [16].

Davidson proposed the HYGARCH (*r*, *d*, *s*) model as follow [12]:

$$\theta(L) = 1 - \frac{\delta(L)}{\beta(L)}(1 + \alpha((1-L)^d - 1)) \quad \alpha \geq 0, d \geq 0, \quad (4)$$

where $\delta(L)/\beta(L)$ is comparison between hyperbolic decay and geometric decay, when $\delta(L)/\beta(L)$ >0. When α<1, these processes are covariance stationary, where L is the lag operator. HYGARCH model is more flexibility in long-run component of modelling the degree of persistence via the memory parameter d Ding and Granger [23].

When d>0, the equation reduces to

$$S = 1 - \frac{\delta(1)}{\beta(1)}(1 - \alpha). \quad (5)$$

FIGARCH and stable GARCH happen when α=1 and α=0, and it means non stationary when α>1 Davidson [12].

When d>1, there is an indication to negative coefficient, which is not permitted.

When d=1, the equation reduces to

$$\theta(L) = 1 - \frac{\delta(L)}{\beta(L)}(1 + \alpha L) \quad \alpha \geq 0. \quad (6)$$

Noted that, the parameter α reduce to an autoregressive root when d=1, and t becomes a stable GARCH or IGARCH depending on α<1 or α=1. Testing the restriction d=1 is the natural way to test geometric and hyperbolic memory, and α>1 is also a legitimate case of non-stationary.

When d is not too large, then

$$\theta(L) = 1 - \frac{\delta(L)}{\beta(L)}\left(1 - \alpha\emptyset(L)\right), \quad (7)$$

where

$$\emptyset(L) = \zeta(1+d)^{d-1}\sum_{j=1}^{\infty} j^{-1-d} L^j, d > 0, \quad (8)$$

$\zeta(.)$ is Riemann zeta function.

When 0<d≤1, it means hyperbolic decaying memory and geometric decaying memory with the former being defined as long memory, then d=1, the conditional variance model becomes an ordinary GARCH model Kwan *et al*. [24].

IV. Result

The results in Table I showed that only XOP and PBW have positive mean. PBW also has the lowest standard deviation. For both unrenewable and renewable energy ETFs have negative skewness and leptokurtic distribution. Their means have high risk to invest in both ETFs. The significant Jarque-Bera Statistic for residual normality shows that unrenewable and renewable energy ETFs are under a non-normal distribution.

This article uses the minimum Akaike Information Criterion (AIC) to classify the orders of ARFIMA, ARFIMA-FIEGARCH and ARFIMA-HYGARCH models. This study used the ARCH Lagrange Multiplier Test (ARCH-LM) to test the ARCH effect. For testing unit root makes clear for the variables having stationary or non-stationary, and this study uses Augmented Dickey Fuller (ADF) proposed by Dickey and Fuller [25].

TABLE I: The Descriptive Statistics of Variables

ETFs	Index	Code	Inception Period	Obs.	Mean	Std. Dev.	Skew.	Kurt.	J-Bera
Unrenewable Energy ETFs	First Trust ISE Revere Natural Gas Index Fund	FCG	2007/5/14	1864	-0.015	2.463	-0.530	5.830	2726.8 ***
	First Trust ISE Revere Natural Gas Index Fund	ADJ FCG	2007/5/14	1864	-0.013	2.463	-0.526	5.851	2744.7 ***
	Market Vectors Global Coal Index	KOL	2008/1/15	1701	-0.051	2.955	-0.588	6.125	2757.2 ***
	Market Vectors Global Coal Index	ADJ KOL	2008/1/15	1701	-0.046	2.956	-0.591	6.131	2762.8 ***
	SPDR S&P Oil & Gas Exploration & Production ETF	XOP	2006/6/22	2099	0.026	2.469	-0.584	8.968	7153.1 ***
	SPDR S&P Oil & Gas Exploration & Production ETF	ADJ XOP	2006/6/22	2099	0.029	2.468	-0.583	8.951	7125.8 ***
Renewable Energy ETFs	Guggenheim Solar ETF	TAN	2008/4/15	1635	-0.122	3.469	-0.290	4.921	1672.8 ***
	Guggenheim Solar ETF	ADJ TAN	2008/4/15	1635	-0.110	3.456	-0.284	4.995	1721.4 ***
	PowerShares WilderHill Clean Energy Portfolio	PBW	2005/3/3	2350	0.028	1.350	-0.612	11.616	13359 ***
	PowerShares WilderHill Clean Energy Portfolio	ADJ PBW	2005/3/3	2350	0.030	1.351	-0.619	11.583	13286 ***

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

In Table II, all significant ADF test, results shows stationary and appropriate for further testing. This study applied the minimum value of AIC to identify the optimal model of ARMA. By using the LM test, this study observes whether the residuals have series correlation or not. The results showed that the entire variables were insignificant except XOP and ADJ XOP, suggesting that we can accept the null hypothesis of no autocorrelation and all of them have the effectiveness. To test the ARCH effect, this paper uses the ARCH-Lagrange Multiplier test (ARCH-LM) Engle [7]. The results showed that all rejected the null hypothesis, indicating that all samples have heteroscedasticity.

TABLE II: SUMMARY STATISTICS OF UNIT ROOT, ARMA, LM, ARCH-LM

ETFs	Code	ADF	ARMA	AIC	LM	ARCH-LM
Unrenewable Energy ETFs	FCG	**-43.857*****	(2,2)	4.639	1.393	**66.963*** **
	ADJ FCG	**-43.890** ***	(2,1)	4.643	0.370	**71.374** ***
	KOL	**-40.256** ***	(2,2)	5.006	2.479	**121.814** ***
	ADJ KOL	**-40.253** ***	(0,1)	5.007	5.258	**119.11** ***
	XOP	**-35.615** ***	(2,2)	4.640	7.188**	**140.757** ***
	ADJ XOP	**-35.617** ***	(2,2)	4.640	6.917**	**139.961** ***
Renewable Energy ETFs	TAN	**-37.672** ***	(1,0)	5.327	2.724	**179.265** ***
	ADJ TAN	**-37.663** ***	(0,1)	5.316	2.391	**183.001** ***
	PBW	**-38.356** ***	(2,2)	3.430	3.167	**73.984** ***
	ADJ PBW	**-38.356** ***	(2,0)	3.429	2.688	**76.338** ***

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

TABLE III: SUMMARY STATISTICS OF ARFIMA MODELS WITH ALL PERIODS

ETFs	Index	ARFIMA			
		model	d-coeff.	AIC	ARCH-LM
Unrenewable Energy ETFs	FCG	(2,2)	**-0.034 [0.062]** *	4.640	113.75 [0.000] ***
	ADJ FCG	(2,1)	**-0.016 [0.647]** *	4.644	114.29 [0.000] ***
	KOL	(2,2)	**0.139 [0.082]** *	5.009	142.29 [0.000] ***
	ADJ KOL	(0,1)	**0.137 [0.088]** **	5.009	142.61 [0.000] ***
	XOP	(2,2)	**-0.055 [0.002]** ***	4.636	139.49 [0.000] ***
	ADJ XOP	(2,2)	**-0.055 [0.002]** ***	4.635	139.44 [0.000]***
Renewable Energy ETFs	TAN	(1,0)	-0.0182 [0.511]	5.325	66.550 [0.000]***
	ADJ TAN	(0,1)	-0.0147 [0.595]	5.317	67.432 [0.000]***
	PBW	(2,2)	**-0.061 [0.000]** ***	3.426	157.25 [0.000] ***
	ADJ PBW	(2,0)	0.008 [0.788]	3.430	155.40 [0.000] ***

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

TABLE IV: SUMMARY STATISTICS OF ARFIMA-FIEGARCH MODELS WITH ALL PERIODS

ETFs	Index	ARFIMA-FIEGARCH							
		d-Arfima	d-Fiegarch	ARCH (Phi1)	GARCH (Beta1)	EGARCH (Theta1)	EGARCH (Theta2)	AIC	ARCH test:
Unrenewable Energy ETFs	FCG	0.005 [0.857]	**0.623 [0.000]** ***	-0.542 [0.053] *	0.764 [0.000] ***	-0.112 [0.008] ***	**0.160 [0.000]** ***	4.222	2.382 [0.037] *
	ADJ FCG	-0.001 [0.984]	**0.628 [0.000]** ***	-0.519 [0.081] *	0.746 [0.000] ***	-0.113 [0.007] ***	**0.161 [0.000]** ***	4.219	2.426 [0.034] *
	KOL	0.034 [0.232]	**0.649 [0.000]** ***	-0.281 [0.441]	0.661 [0.000] ***	-0.097 [0.004] ***	**0.124 [0.000]** ***	4.368	1.107 [0.355]
	ADJ KOL	0.021 [0.862]	**0.713 [0.000]** ***	1.627 [0.557]	-0.384 [0.048] **	-0.072 [0.042] **	**0.112 [0.064]** ***	4.365	0.207 [0.959]
	XOP	0.111 [0.274]	**0.619 [0.000]** ***	-0.541 [0.026] **	0.742 [0.000] **	-0.135 [0.005] ***	**0.185 [0.000]** ***	4.154	3.310 [0.006] **
	ADJ XOP	0.142 [0.159]	**0.714 [0.000]** ***	0.934 [0.025] **	-0.543 [0.109]	-0.127 [0.009] ***	**0.187 [0.000]** ***	4.154	2.132 [0.059] *
Renewable Energy ETFs	TAN	0.029 [0.505]	0.080 [0.668]	-0.086 [0.896]	0.977 [0.000] ***	-0.032 [0.137]	**0.141 [0.026]** **	5.032	0.524 [0.759]
	ADJ TAN	0.014 [0.643]	**0.686 [0.000]** ***	0.532 [0.235] ***	-0.018 [0.916]	-0.036 [0.085] *	**0.204 [0.021]** **	5.032	0.229 [0.950]
	PBW	-0.03 [0.149]	**0.453 [0.000]** ***	-0.460 [0.000] ***	0.839 [0.000] ***	-0.203 [0.000] ***	**0.097 [0.000]** ***	2.896	1.452 [0.203]
	ADJ PBW	-0.001 [0.982]	**0.462 [0.000]** ***	-0.464 [0.000] ***	0.841 [0.000] ***	-0.201 [0.000] ***	**0.040 [0.000]** ***	2.897	1.341 [0.244]

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

TABLE V: SUMMARY STATISTICS OF ARFIMA-HYGARCH MODELS WITH ALL PERIODS

ETFs	Index	ARFIMA-HYGARCH						
		d-Arfima.	d-hygarch	ARCH (Phi1)	GARCH (Beta1)	Log Alpha (HY)	AIC	ARCH test:
Unrenewable Energy ETFs	FCG	-0.050 [0.536]	**1.070 [0.000]** ***	-0.098 [0.149]	0.937 [0.000] ***	-0.005 [0.272]	4.237	1.236 [0.290]
	ADJ FCG	-0.055 [0.151]	**1.069 [0.000]** ***	-0.097 [0.158]	0.937 [0.000] ***	-0.005 [0.279]	4.234	1.243 [0.286]
	KOL	-0.008 [0.854]	**0.410 [0.001]** ***	0.130 [0.553]	0.474 [0.116]	-0.011 [0.807]	4.387	1.339 [0.245]
	ADJ KOL	-0.004 [0.891]	**0.407 [0.001]** ***	0.12 [0.582]	0.460 [0.124]	-0.013 [0.778]	4.385	1.304 [0.260]
	XOP	-0.110 [0.055] **	0.713 [0.286]	0.076 [0.610]	0.710 [0.194]	-0.028 [0.573]	4.174	2.701 [0.019]*
	ADJ XOP	-0.111 [0.057] **	**0.704 [0.119]**	0.074 [0.444]	0.701 [0.067] **	-0.028 [0.444]	4.173	2.689 [0.020]*
Renewable Energy ETFs	TAN	0.010 [0.791]	**0.682 [0.060]** **	0.119 [0.247]	0.698 [0.019] **	-0.059 [0.302]	5.031	0.323 [0.899]
	ADJ TAN	0.025 [0.466]	**0.626 [0.071]** *	0.157 [0.04] **	0.661 [0.042] **	-0.068 [0.283]	5.025	0.255 [0.938]
	PBW	-0.156 [0.142]	**0.943 [0.000]** ***	-0.082 [0.18]	0.805 [0.000] ***	-0.037 [0.032] **	2.936	0.287 [0.920]
	ADJ PBW	-0.109 [0.023] **	**0.947 [0.000]** ***	-0.081 [0.210]	0.807 [0.000] ***	-0.037 [0.033] **	2.937	0.281 [0.924]

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

TABLE VI: COMPARISON LOG-LIKELIHOOD ARFIMA, ARFIMA FIEGARCH, AND ARFIMA-HYGARCH MODELS WITH ALL PERIODS

ETFs	Code	ARFIMA	ARFIMA-FIEGARCH	ARFIMA-HYGARCH
		Log Likelihood	Log Likelihood	Log Likelihood
Unrenewable Energy ETFs	FCG	-4317.513	**-3922.501**	-3937.710
	ADJ FCG	-4317.134	**-3920.790**	-3936.470
	KOL	-4253.187	**-3702.890**	-3720.357
	ADJ KOL	-4253.739	**-3703.099**	-3721.590
	XOP	-4857.971	**-4347.268**	-4369.126
	ADJ XOP	-4857.934	**-4347.711**	-4368.785
Renewable Energy ETFs	TAN	-4347.478	**-4104.903**	-4105.006
	ADJ TAN	-4342.203	-4104.949	**-4100.736**
	PBW	-4018.801	**-3391.301**	-3438.932
	ADJ PBW	-4025.377	**-3394.021**	-3441.546

The results of the ARFIMA model in Table III showed that the variable is stationary with d-coefficient between -0.5 < *d*-coeff < 0.5, revealing that there were significant long memory for KOL and ADJ KOL in unrenewable energy ETFs and ADJ TAN and ADJ PBW in renewable energy ETFs Paul *et al*., [18]. On the other hand, there is a presence anti-persistence for others ETFs. Furthermore, the testing results of ARCH-LM test found that no arch effect for all samples was rejected.

In Table IV, by using ARFIMA-FIEGARCH model this study found that all data samples were stationary because |Φ|EGARCH<1 and |*d*|-Arfima<0.5 Zaffaroni [22]. Thus, d-FIEGARCH showed that unrenewable energy ETFs and renewable energy ETFs have strong volatility persistence because of 0<*d*<1. EGARCH (Theta 1) revealed that both energy ETFs have negative innovations inducing higher volatility than positive innovations, because of θ<0, proposes by Christensen *et al*. [20]. Moreover, θ (Theta 1) also explains asymmetry in news impact on volatility. In Table 4 showed that all samples for θ have a negative effect and revealed that negative news impacted on volatility on both energy ETFs.

The results of ARFIMA-HYGARCH model can be seen in Table V, all data samples are stationary because d-ARFIMA showed -0.5<*d*<0.5 Paul *et al*., [18]. Furthermore, when Log α<1 reduces to an autoregressive root, it becomes more stable than GARCH or IGARCH. Moreover, the results showed that all data samples have long memory except FCG, ADJ FCG because of 0<*d*-hygarch≤1 Kwan *et al*., [24]. Nonetheless, FCG and ADJ FCG result really close to d-hygarch=1, revealing that all data have roughly long memory.

Used Log-likelihood result compared three models for testing of long memory as shown in Table VI. The log likelihood value is always negative. When log likelihood has higher value, and closer to zero, this indicated a better fitting model Johnston and Di Nardo, 1997; Fox [26]- [27] The bigger Log-likelihood measurement showed that ARFIMA-FIEGARCH model is the best model to reveal long memory for both energy ETFs except for ADJ TAN having better result by using ARFIMA-HYGARCH.

V. Conclusions

In this paper have been used three models such as ARFIMA, ARFIMA-FIEGARCH, and ARFIMA-HYGARCH to analyze the long memory in volatility, and leverage effects of renewable and unrenewable energy exchange-traded funds (ETFs). Furthermore, this study used original price and adjustment price returns for both renewable and unrenewable energy ETFs. The results found that using adjustment price return is similar with the original price return. Both energy ETFs have long memory in volatilities and asymmetric effect. Moreover, ARFIMA–FIEGARCH model is the best to analyze long memory and asymmetric volatility among others except for ADJ TAN. With the research *d*-FIEGARCH showed that both energy ETFs have strong volatility persistence due to $0<d<1$, and the results of ARFIMA–FIEGARCH revealed that both energy ETFs have negative news impact on volatility.

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