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Measuring the Market Efficiency of Energy Exchange-Traded Funds (ETFS)

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Abstract

This paper examines the market efficiency of Energy Exchange-Traded Funds (ETFs) of both renewable and unrenewable energy ETFs. We adopt GARCH modelling approach to investigate the long-range dependence in ETFs volatility. Specifically, we estimate a FIGARCH model proposed by Baillie *et al.* (1996) using daily returns. We find evidence of long memory dependence in all ETFs, implying that, all the indexes under investigation are weak-form inefficient. The results also indicate that the volatility has a predictable structure in all the ETFs of both renewable and unrenewable energy ETFs, indicating the potential of diversification for the international investors.

Keywords

Energy Exchange-Traded Funds, Market Efficiency, FIGARCH, Temporal Dependencies, Long Memory

1. Introduction

Most existing literature focus on investigating long-term memory in stock markets returns, fixed income markets returns, or commodity markets returns. Mixed results were found on the presence of apparent temporal dependencies in financial market volatility. Several studies conclude that capital markets are characterized by long memory processes [1]-[6]. However, many studies do not find any significant and robust evidence of positive long-term persistence in the financial markets [7]-[12]. Simultaneously, other stream of literature finds temporary or little evidence of long-term memory in different stock markets [7]-[21].

Moreover, studies that investigate the temporal dependencies in financial market volatility, employ various methodologies such as, classical rescaled-range

(R/S) analysis [22] [23], modified rescaled-range (R/S) analysis [13], the spectral regression method [24], and different GARCH specifications. However, a systematic review of the literature indicates that FIGARCH models outperform many of the other conditional heteroscedastic models in predicting and modeling different classes of assets, such as stock returns [25] [26], exchange rate returns [27] [28] [29], and futures returns [30] [31] in different market settings. Again, as per the best of authors' knowledge, not sufficient applications of volatility models are available in the existing literature.

We believe that the existing literature on investigating market efficiency and/or inspecting the temporal dependencies lead to very different or even contradicting conclusions, and hence still need further examination. And, surprisingly, the Energy Exchange-Traded Funds (ETFs) do not attract the attention of researchers despite its diverse nature and potential for future investors.

This study aims at investigating the market efficiency of ETFs. We estimate FIGARCH model proposed by Baillie *et al.* [27] to examine the long memory characteristics in the ETFs volatility of both renewable and unrenewable energy ETFs using daily returns calculated by Thomson Reuters Eikon. We use nine major indexes of renewable and unrenewable energy ETFs, namely, the Fidelity MSCI Energy Index ETF (FENY), First Trust Energy AlphaDEX Fund (FXN), iShares US Oil & Gas Exploration & Production ETF(IEO), iShares Global Energy ETF (IXC), iShares US Energy ETF (IYE), SPDR S&P North American Natural Resources ETF (NANR) and VanEck Vectors Oil Services ETF (OIH), Vanguard Energy Index Fund ETF (VDE), Energy Select Sector SPDR Fund (XLE), to inspect the temporal dependencies in depth.

We adopt FIGARCH model to investigate the long-range dependence in ETFs volatility of both renewable and unrenewable energy ETFs. We find evidence of long-term memory in the volatility of all the ETFs. This implies that all the ETFs under investigation are weak-form inefficient funds. The results also indicate that the volatility has a predictable structure in all the ETFs of both renewable and unrenewable energy ETFs, indicating the potential of diversification for the international investors. We argue that a better understanding of the long-range dependence in ETFs volatility (long memory processes), within the EFTs market, is inevitable for international investors, multinational corporations, and portfolio managers, to achieve superior diversification and manage their financial risk exposure.

The rest of the paper is organized as follows: next section describes the FIGARCH model used to study long-range dependence in EFTs returns. Section 3 provides a detailed outlook of the data. In Section 4, we present and discuss the results of the empirical analysis and finally Section 5 concludes the paper.

2. Model Specifications

The Autogressive Conditional Heteroscedasticity (ARCH) process proposed by Engle [32] and generalized ARCH (GARCH) by Bollerslev [33] are well known for volatility modeling and forecasting of stock returns. More precisely, to model the most prominent features of the time series data (also called stylized facts) such as volatility clustering, excess kurtosis, and fat-tailedness. However, to explain how persistent volatility is, GARCH process can easily be extended to identify the long memory process, a common observation in actual data, through a fractionally integrated procedure proposed by Baillie *et al.* [27]. Specifically, the Fractionally Integrated Generalized Autoregressive Conditional Heteroscedastic (FIGARCH) process.

We start our empirical specification with the GARCH (p, q) process introduced by Bollerslev [33], we can write the conditional variance as:

$$h_t = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

The primary constraint of this model is that all the expounding variables must be positive *i.e.*, $w, \alpha, \beta \geq 0$ this is known as the non-negativity restriction. Further, for stationarity we require that $\alpha + \beta$ is less than unity. However, if this restriction violates, *i.e.*, $\alpha + \beta \geq 1$ we conclude that the shocks are persistent. Hence, to account for the persistency of shocks an IGARCH (1, 1) model proposed by Engle and Bollerslev [34] can be written as

$$h_t = w + \sum_{i=1}^{q} (1 - \beta_i) \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$

where $0 \triangleleft \beta_i \triangleleft 1$.

The IGARCH model implies infinite persistence of the conditional variance to a shock in squared returns. The IGARCH process can also be illustrated as an ARMA (m, p) process

$$\varphi(L)(1-L)\varepsilon_t^2 = w + [1 - \beta(L)]v_t$$

The fractionally integrated GARCH or FIGARCH class of models is obtained by replacing the first difference operator (1 − L) in above model with the fractional differencing operator (1 − L)d. where d is a fraction $0 < d < 1$. Thus, the FIGARCH class of models can be obtained by considering following equation.

$$\varphi(L)(1-L)^d \varepsilon_t^2 = w + [1 - \beta(L)]v_t$$

The FIGARCH process identifies potential presence of long memory or the subsistence of dependencies in financial time series mainly due to the hyperbolically decaying autocorrelation function, or in other words, long memory process can be illustrated through a fractionally integrated procedure, Meanings, the level of integration is fewer than one however superior than zero, implying that the impact of a shock continue over an extensive period of time. The main advantage of FIGARCH process is that it allows for long memory in the conditional variance which is characterized by the fractional integration parameter d and the short-term dynamics can be modeled through the traditional GARCH parameters. Following Baillie *et al.* [27] we adopt the Quasi maximum likelihood estimation (QMLE) technique.

3. Data and Descriptive Statistics

The data comprise daily returns of both renewable and unrenewable energy ETFs. We use nine major indexes of renewable and unrenewable energy ETFs (namely, the Fidelity MSCI Energy Index ETF (FENY), First Trust Energy AlphaDEX Fund (FXN), iShares US Oil & Gas Exploration & Production ETF(IEO), iShares Global Energy ETF (IXC), iShares US Energy ETF (IYE), SPDR S&P North American Natural Resources ETF (NANR), VanEck Vectors Oil Services ETF (OIH), Vanguard Energy Index Fund ETF (VDE), Energy Select Sector SPDR Fund (XLE), to inspect the temporal dependencies in depth.

The beginning of the sample period is dictated by the availability of data for each index investigated. The end of the period is May 2017 for all indices. Figure 1 shows the development of different indexes of both renewable and unrenewable energy ETFs. All the data are retrieved from Thomson Reuters Eikon and daily returns are constructed as the first difference of logarithmic prices multiplied by 100.

Before formal investigation of long memory in energy ETFs, we inspect the time-series properties of our data set using primary techniques, for instance, Stationarity in the time series is checked by applying the Augmented Dickey Fuller (ADF) test. To check the null hypothesis of normal distribution we calculate Jarque-Bera test statistic. Finally, to investigate the null that autocorrelation coefficients up to 20 lags are zero, we compute Ljung and Box [35] test statistic, together with the ARCH LM-statistic (five lags) on each returns series. The results shown in Table 1, in general, support the findings of prior studies and allow us to reject the null hypothesis that returns have unit root in favor of alternate hypothesis of stationarity, P-Values are reported in the table (even at 1% MacKinnon critical value). The Jarque-Bera normality and Engle's Lagrange Multiplier ARCH tests both revels that the return data of all the energy ETFs exhibit non-normality and ARCH effects, P-Values are reported in the table. These primary findings grant confirmation against the market efficiency hypothesis and allow us to use GARCH specification through LB statistics and ARCH LM-statistic.

4. Empirical Results

Using the Energy Exchange-Traded Funds, we re-examine the subject of whether or not actual returns reveal temporal dependence. We utilize both renewable and unrenewable energy ETFs. Our empirical investigation is based on the GARCH family models. First, to model the volatility dynamics of ETFs, we utilize the traditional GARCH (1, 1) model. Second, to check the volatility persistence, we adopt IGARCH (1, 1) technique. Finally, to investigate the long run dependence in ETFs, we employ FIGARCH (1, 1) framework. The results of estimated GARCH, IGARCH and FIGARCH models are reported in Table 2.

Panel A of Table 2 presents GARCH (1, 1) estimations of all the ETFs under investigation. The results show that both the ARCH and GARCH parameters

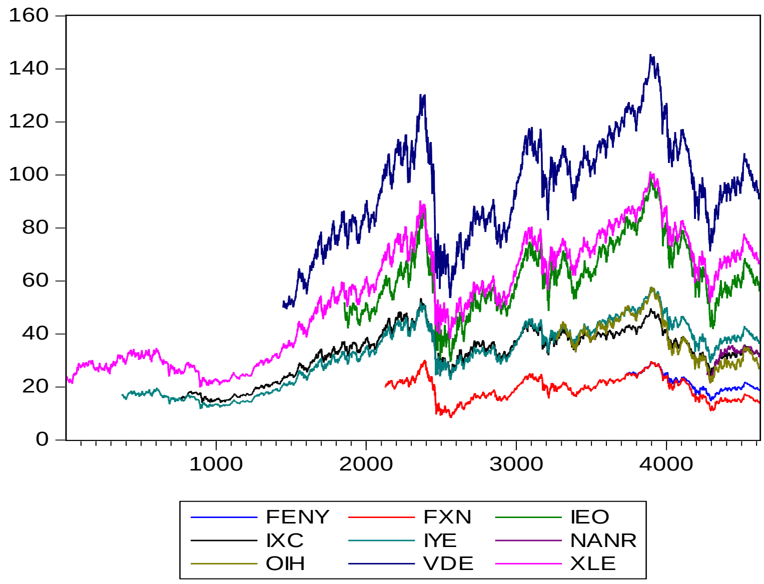

Figure 1. Development of different energy ETFs.

Table 1. Descriptive statistics of Energy Exchange-Traded Funds for the daily return indices.

Panel A: Summary statistics									
Index	Mean	Std. dev.	Skewness	Kurtosis	J-B test	ADF	Q-Stat	ARCH−LM	Obs.
FENY	21.865	3.525	0.362	2.143	<0.001	<0.001	<0.001	<0.001	890
FXN	19.352	4.518	−0.006	2.407	<0.000	<0.000	<0.000	<0.000	2497
IEO	62.059	13.229	0.302	2.879	<0.000	<0.000	<0.000	<0.000	2771
IXC	33.008	9.059	−0.481	2.452	<0.000	<0.000	<0.000	<0.000	3860
IYE	32.258	11.737	−0.157	1.907	<0.000	<0.000	<0.000	<0.000	4247
NANR	32.002	3.498	−1.461	4.038	<0.000	<0.000	<0.000	<0.000	349
OIH	38.404	8.407	0.218	2.164	<0.000	<0.000	<0.000	<0.000	1352
VDE	94.992	20.325	−0.027	2.529	<0.000	<0.000	<0.000	<0.000	3174
XLE	53.948	21.507	0.001	1.745	<0.000	<0.000	<0.000	<0.000	4623

Panel B: Pair wise sector correlations								
Index	FENY	FXN	IEO	IXC	IYE	NANR	OIH	VDE XLE
FXN	0.957	1.000						
IEO	0.978	0.957	1.000					
IXC	0.989	0.933	0.965	1.000				
IYE	1.000	0.959	0.976	0.988	1.000			
NANR	0.904	0.830	0.839	0.921	0.906	1.000		
OIH	0.945	0.942	0.940	0.929	0.944	0.780	1.000	
VDE	1.000	0.956	0.980	0.990	0.999	0.905	0.946	1.000
XLE	0.997	0.944	0.983	0.990	0.996	0.898	0.942	0.998 1.000

Table 2. Long memory in ETFs market volatility, estimated from a univariate GARCH (1, 1), IGARCH (1, 1) and FIGARCH (1, 1) model of daily return indices.

Panel A: GARCH(1, 1) estimations									
Parameters	FENY	FXN	IEO	IXC	IYE	NANR	OIH	VDE	XLE
μ	−0.047	0.015	0.033	0.015	0.019	0.010	0.019	0.013	0.018
ω	0.015	0.019*	0.023*	0.013*	0.017*	−0.005	0.007	0.016*	0.014*
α	0.082*	0.074*	0.075*	0.071*	0.074*	0.010	0.049*	0.070*	0.066*
β	0.909*	0.923*	0.919*	0.922*	0.918*	0.991*	0.949*	0.923*	0.927*
b3	−0.397*	−0.540*	−0.455*	−0.713*	−0.612*	−0.096*	−0.395*	−0.545*	0.479*
b4	4.590*	3.316*	2.726*	4.553*	3.472*	3.868*	2.865*	2.038*	1.794*
Q(20)	13.347	21.686	20.569	15.771	21.936	11.650	19.381	19.848	21.204
Q2(20)	13.364	36.337	29.700	26.797	16.008	14.693	10.128	10.291	11.507
Panel B: IGARCH(1, 1) estimations									
Parameters	FENY	FXN	IEO	IXC	IYE	NANR	OIH	VDE	XLE
μ	−0.048	0.014	0.033	0.014	0.022	0.009	0.101	0.058	0.119
ω	0.012*	0.017*	0.018*	0.010*	0.012*	−0.005*	0.184*	1.071*	1.146*
β	0.911*	0.924*	0.919*	0.924*	0.920*	0.989*	0.634*	0.020*	0.081*
d	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
b3	−0.433*	−0.542*	−0.461*	−0.725*	−0.617*	−0.117*	0.064*	−0.664*	1.018*
b4	4.676*	3.363*	2.766*	4.622*	3.569*	3.863*	2.752*	2.662*	4.687*
Q(20)	13.054	21.622	20.304	15.697	21.695	11.474	15.700	21.394	28.173
Q2(20)	13.093	35.714	29.500	25.720	15.452	14.623	13.457	12.273	60.278
Panel C: FIGARCH(1, 1) estimations									
Parameters	FENY	FXN	IEO	IXC	IYE	NANR	OIH	VDE	XLE
μ	−0.002*	0.015	0.030	0.013	0.021	0.002	0.035	0.054	0.080
ω	0.020*	0.040	0.023*	0.017*	0.015*	−0.018	−0.274*	−0.309	−0.130
β	0.507*	0.524*	0.896*	0.870*	0.901*	0.338*	0.017	0.116	0.015
d	0.484*	0.575*	0.950*	0.899*	0.962*	0.341*	0.103*	0.134*	0.115
b3	−0.519*	−0.613*	−0.473*	−0.721*	−0.624*	−0.242*	−0.263*	−0.629*	0.697
b4	5.299*	3.878*	2.810*	4.639*	3.640*	3.297*	2.707*	1.786*	2.399
Q(20)	13.231	22.633	19.761	14.784	21.376	10.468	20.817	23.704	26.763
Q2(20)	11.424	31.403	28.798	21.429	15.818	19.793	13.914	12.146	22.960

(α and β) are statistically significant for all the ETFs under investigation, which confirm the existence of the time-varying conditional variance. It is also evident from Panel A of Table 2 that the parameters of the conditional variance equations are all positive and meet the positivity constraint for the GARCH (1, 1) specification. However, the sum of α and β parameters is very close to the unity, indicating the persistence of the volatility in all the indices. One shortcoming of the traditional GARCH model is its failure to capture long-range dependence or to account for persistence of volatility in the data. Hence, we utilize IGARCH process proposed by Engle and Bollerslev [34]. The IGARCH model implies infinite persistence of the conditional variance to a shock in squared returns. Panel B of **Table 2** presents IGARCH (1, 1) estimations of all the ETFs under investigation. The results are very similar to the standard GARCH (1, 1) estimations presented in Panel A, confirming the temporal dependencies in all the ETFs.

Finally, FIGARCH (1, 1) model is employed in order to investigate the existence of possible temporal dependencies in the volatility of all the ETFs under investigation. The FIGARCH process identifies potential presence of long memory or the subsistence of dependencies in financial time series mainly due to the hyperbolically decaying autocorrelation function. Results from this model are shown in Panel C of **Table 2**. As per our results, the fractional differencing parameter, d, is found to be significantly different from zero and is within the theoretical value (*i.e.*, $0 < d < 1$). This indicates that the volatility of all the ETFs under investigation clearly exhibits a long memory process. It is our connotation that our findings show the importance of modelling long memory in volatility and suggests that future volatility depends on its past realizations and, as a result, is predictable. Our findings also support the findings of prior studies on both stock and commodity markets.

To conclude, we report the sample skewness and kurtosis for the standardized residuals, (denoted by b3 and b4 in **Table 2**), also Ljung-Box portmanteau tests for up to 20th-order serial correlation in the standardized and the squared standardized residuals (denoted by Q20 and Q220 in **Table 2**) as diagnostic tests for all three models. While comparing different GARCH family models based on diagnostic tests, we found FIGARCH model performs better than the other two models, which is again consistence with the most recent prior research on the topic.

In summary, we provide evidence of long memory in the volatility of all the ETFs, which suggest that, all the ETFs under examination are week form inefficient. This is an evidence of violation of efficient market hypothesis, which can lead to the arbitrage opportunities for international investors who are interested to invest in one of the fastest growing market—Energy Exchange-Traded Funds. Furthermore, our results confirm that the volatility has a predictable structure in all Energy Exchange-Traded Funds, indicating the need of regulatory and economic reforms within the Energy Exchange-Traded Funds system.

5. Conclusion

In this study, we attempt to re-examine the market efficiency of Energy Exchange-Traded Funds. Specifically, we look at the long memory in ETFs market volatility. To inspect the temporal dependencies in depth we utilize nine major ETFs, representing both renewable and unrenewable EFTs. To study the long memory we estimate FIGARCH model proposed by Baillie *et al.* [27] using daily returns calculated by Thomson Reuters Eikon. We find evidence of long memory in the volatility in all the ETFs. This implies that all the ETFs under investigation are week form inefficient. Our results show that the volatility in different ETFs has a predictable structure. Our results indicate the need of regulatory and economic reforms within the Energy Exchange-Traded Funds system. As per our empirical investigation FIGARCH model performs better than the tradition GARCH models.

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