Jump Dynamics and Leverage Effect: Evidences from Energy Exchange Traded Fund (ETFs)

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Abstract

This paper is concerned with the behavior of energy ETF prices. It applies three models: autoregressive moving average (ARMA) and generalized autoregressive conditional heteroskedasticity (GARCH), along with their revised forms, ARMA–Exponential-GARCH, Glosten-Jagannathan-Runkle (GJR), and GARCH diffusion process with jump models. This study looks at the volatility behavior and jumps dynamics of Energy and Master Limited Partnership's (MLP) ETFs. The results show that ARMA-GARCH is appropriate for modeling energy and MLP ETFs. Both ETFs offer positive leverage and asymmetric volatility. The results show that the jump model with a GARCH volatility specification has an actual amount of jump presence and time variation in the jump size distribution. The conclusion of the ARMA - EGARCH model gives evidence of the reverse leverage effect. The leverage term positively influences the conditional variance, while the asymmetry coefficient for the GJR model is positive and significant. These results reveal that both Energy and MLPs ETF have high volatility.

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1. Introduction

Exchange Traded Funds (ETFs), which replicated the performance of certain benchmark indexes by owning a diverse group of assets such as stocks, equities, commodities, or bonds, have become popular investment vehicles in modern finance. Investing in ETFs, relative to individual stocks, helps investors reduce unsystematic risks and provides knowledge to market indices and industries. ETFs often have lower management costs and are more transparent and flexible. Energy ETFs have become popular among investors, government officials, and policymakers due to global energy transformation. An energy economy based on everyday living depends on a reliable and affordable supply of energy products. For example, market recessions, high inflation, lack of productivity, and slowing economic growth have been related to the energy sector, particularly regarding the volatility of crude oil and gas prices.

Energy ETF is engaged in energy exploration and production. An energy ETF database, which is traded on the US exchanges, has $79.98 billion of assets under management (ETF.com). Many companies have invested directly in energy sectors for attractive development projects to create new enterprises. The energy stock market is an interesting investing preference. Price shocks in the energy market would be of tremendous concern to investors and regulators due to the significant impact on the financial sector. Energy ETFs and Master Limited Partnership (MLP) are closely linked. Limited partnerships are publicly traded limited partnerships that primarily control oil and gas assets and offer tax advantages to their investors. MLPs have received little attention from either academics or literature.

Barsky and Kilian (2004), Du et al. (2010), Acaravci et al. (2012), and Ordu and Soytaş (2016) revealed that there is a strong relationship between energy crude oil prices and macroeconomic settings. Rising energy prices have increased business input costs, resulting in lower profitability and productivity and impacting a country's macroeconomic situation. As a result, such a rise in energy costs increases the borrowing cost for businesses and negatively impacts financial markets. On the other hand, rising energy prices also strengthen inflationary pressure on the public sector and contribute to high-interest rates (Sadorsky, 1999).

Energy market volatility influences the global economy and financial market stability (Wang et al. 2016; Amelie and Darne 2017; and Gong and Lin 2018). Investors, fund managers, and risk managers need to understand the empirical implications of a large energy ETF. Several studies have examined the mechanism of volatility transmission in various markets (Dornbusch, Park, and Claessens, 2000; Bae, Karolyi, and Stulz, 2003; and Tang and Xiong 2012). The stock market volatilities' transmission was quantified using basic cross-market correlation coefficients or Probit models. Another way to test volatility transmission is to use the ARCH (Engle, 1982) or GARCH (Bollerslev, 1986) to evaluate the variance-covariance transmission mechanism. Popular specifications include the multivariate extension of the model presented by McAleer, Hoti, and Chan (2009), the matrix-exponential of GARCH presented by (Kawakatsu, 2006), and the asymmetric Baba

Engle Kraft Kroner (BEKK) model based on Engle and Kroner (1995) and Kroner and Ng (1998).

Time series of financial returns are conditionally heteroscedastic as volatilities respond asymmetrically to historical returns. Volatility levels tend to be higher in response to previous negative shocks (that is, bad news) than in response to positive shocks (good news), known as leverage (Black, 1976). The presence of leverage in ETF markets is an unsolved issue that has piqued the curiosity of academics over the past decade. Most empirical research on the subject of volatility asymmetry or leverage effect utilizes the same technique, which is based on matching numerous asymmetric GARCH-type models to financial returns and assessing the statistical significance of the coefficient representing the leverage effect. Kristoufek (2014), Chkili et al. (2014), Chang (2012), and Wu et al. (2012) have provided empirical findings that examine the energy commodities, including West Texas Intermediate (WTI) and Brent crude oils, heating oil, and natural gas for leverage effect.

This study aims to investigate the effect of volatility on one of the most popular investment vehicles in the energy industry: ETFs. This study develops a novel methodology for analyzing the volatility asymmetry and leverage effect on Energy and MLPs ETFs utilizing an ARMA-GARCH, ARMA-EGARCH, ARMA-GJR, and GARCH-Jump model. ETF Energy and MLPs display clustering volatility and Jump behavior. It will eventually lead to even greater movements in ETF prices. To our knowledge, this research on MLP and Energy ETFs focuses on the importance of investor investment decisions. The study is driven by the gap and looks at how ETFs impact investment decisions and risk.

Both Energy and MLP ETF returns are asymmetric with a leverage effect. The findings show that negative shocks to ETF returns have a larger impact than positive shocks. The fact that an ETF jump has different effects on different ETFs. Both ETFs statistics show a large number of jumps. The impact of jumps can be perceived in variations in asset prices in financial applications. This study provides a generalization and a step forward by finding evidence for jumps and leverage effects in the Energy and MLPs ETFs. Investors and risk managers are concerned about risks, particularly when they involve significant price movements and volatility shocks. As a result, scholars and market practitioners are fascinated by return jump events. By examining the metrics, this study hopes to uncover channels of information flow and explain the price discovery process between financial markets and energy ETFs. From an investment perspective, this information would facilitate efficient portfolio construction and cover volatility in the energy sector. The empirical results should contribute to a regulatory perception and an understanding of the possible mechanism for transmitting risks between the entire financial market and the energy sector.

The body of this article is organized according to the following. The second part presents the relevant literature. Section 3 deals with data selection and methodology, whereas Section 4 deals with empirical results. Section 5 concludes the findings and their implications.

2. Literature Review

The empirical evidence that energy price shocks are closely linked to macroeconomic performance has been a longstanding concern for economists. Since the 1970s, it has been widely recognized that energy prices have responded to the economic dynamics influencing stock prices. Investors know that ETFs contribute to reducing systemic risk and have become a critical source of financial market information. Alexopoulos (2018) reviewed energy ETF performance and found that all ETFs outperform. Chang et al. (2018) used generated regressors and a multivariate conditional volatility model to examine the spillover effects of the US energy and financial sectors in the spot and futures markets. The empirical evidence indicates a positive impact between the financial and Energy ETF. It states that there is an optimal portfolio to hedge capital market risks. Chang and Ke (2014) used the Vector Autoregressive (VAR) model and examined the relationship between returns and flows for five ETFs in the US energy sector. They discussed four assumptions: price pressure, reporting, feedback trading, and smoothing. The empirical evidence only argues for the smoothing hypothesis. Baum et al. (2021) looked into the similarities and differences between energy commodities markets by using the Generalized Method of Moments (GMM) approach. The study concluded that the jumps and leverage model is best suited for the volatility of future natural gas and stock index returns.

Hamilton (2003), Hammes and Wills (2005), and Benkraiem et al. (2018) examined the connection between the S&P 500 Index and energy prices such as West Texas Intermediate (WTI), gasoline, heating, diesel, and natural gas prices to highlight the influence of energy price shocks on financial market prices. According to the Quantile Autoregressive Distributed Lags (QARDL) model, the results suggest that crude oil and natural gas are important economic factors in explaining equity markets' short- and long-term volatility. Bastianin and Manera (2018) used a structural vector autoregressive model to examine the reaction of US equity market volatility to three different structural oil market volatilities. Their findings revealed that stock market volatility had been heavily affected by oil price shocks brought about by unforeseen changes in global and oil-specific demand. Based on an autoregressive structural vector model, Kang et al. (2017) evaluated the effect of oil price shocks and economic policy uncertainty on the stock returns of oil and gas industries. Empirical findings revealed that oil demand shocks significantly impact oil and gas company returns, but political uncertainty shocks have a negative impact. Mason and Wilmot (2014) looked into the possibility of a jump in natural gas prices, including the Henry Hub spot price in the US and the National Balancing Point spot price in the UK. They found solid empirical evidence of jumps for both markets. However, jumps seem to be larger in the United Kingdom. With the Jump diffusion process and changing volatility over time, they found that a model containing stochastic volatility and leverage is best suited for future natural gas. Chen et al. (2019) investigated the relationship between oil returns and volatility transmission using daily spot returns in the crude oil markets with a focus on the leverage effect

on risk measures like value at risk (VaR) and Conditional Value at Risk (CvaR). The traditional Stochastic Volatility (SV) model associated with customarily distributed errors produced the best predictions in out-of-sample studies and has a leverage effect.

Yang et al. (2022) used a multivariate Hawkes process modeling technique by examining Intraday high-frequency market data. They developed a contagion jump modeling framework to study the contagion effect of market jumps in energy ETFs. He reported that the negative index jumps to the front of the index market price processes. Baum and Zerilli (2016) demonstrated a surge in the crude oil futures market. This article also looked at how Jumps and leverage affect risk management for individual investors and businesses looking to manage risk in terms of realized volatility jumps while minimizing their capital.

3. Data and Methodology

On transparency and price flexibility, Energy ETFs have always performed well and are considered the top investment vehicle in the world. This study used Energy ETFs and MLPs ETFs, generally traded on the US ETFs market. A total of 32,829 observations covering the period from 2 May 2012 to 29 April 2022 are extracted from the website "Yahoo Finance" database. This work employs six Energy ETFs and six MLPs ETFs, as shown in Table 1. This document uses the closing price of ETFs to ensure consistency across day-to-day data. To better understand the data based on their operations, it divides them into two categories, Energy ETFs and MLP ETFs.

Table 1: The summary and inception period of Energy and MLPs ETF

Types	ETF	Ticker	Inception Date
Energy ETFs	iShares Global Energy ETF	IXE	2012.05.02-2022.04.29
	iShares U.S. Energy ETF	IYE	
	VanEck Oil Services ETF	OIH	
	Vanguard Energy ETF	VDE	
	Energy Select Sector SPDR Fund	XLE	
	SPDR S&P Oil & Gas Exploration & Production ETF	XOP	
MLPs ETFs	iShares U.S. Oil & Gas Exploration & Production	IEO	2012.05.02-2022.04.29
	iShares MSCI Global Energy Producers	FILL	
	InfraCap MLP ETF	AMZA	2014.03.10-2022.04.29
	First Trust North American Energy Infrastructure Fund	EMLP	2012.06.22-2022.04.29
	Global X MLP ETF	MLPA	2012.05.02-2022.04.29
	Global X MLP & Energy Infrastructure ETF	MLPX	2013.08.08-2022.04.29

The Energy ETF refers to the energy industry, such as crude oil and Brent gas refining, fuels, solar and wind, etc. Master Limited Partnerships (MLPs) focus on operating companies that frequently transport and process energy products such as oil, natural gas, refined products, and natural gas liquids (NGLs). ETFs often offer attractive dividends. The statistical features of the data clustering series are visualized in Figure 1. The trend to higher volatility over a period will be followed by higher volatility in the following period. This study uses the GARCH model to overcome the phenomenon.

3.1 Auto Regressive and Moving Average Model (ARMA) model

The Auto-regressive Moving Average (ARMA) model was created by Box and Jenkins (1976) to express the relationship between current and past variables. The AR model indicates that the variable y_t can be affected by the error term ε_t, and influenced by its own lagged variables. The ARMA (p, q) model is represented by:

$$y_t = a_0 + \sum_{i=1}^{p} a_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} b_i \varepsilon_{t-i}. \tag{1}$$

where a_0 represents a constant intercept term; p denotes the number of lagged periods; a_i is the coefficient of y_{t-i}; ε_t Stands for the error term. This paper breaks down the model of the symmetrical and asymmetrical functions. The ARCH and GARCH models are known to be symmetric functions, while the asymmetric function consists of EGARCH, GJR-GARCH, and Jump models. These models apply to measure asymmetry and volatility behavior between Energy and MLPs ETFs.

3.2 Symmetric Model

As the residual variability was fixed in classical models, Engle (1982) developed the ARCH model, allowed residual variations over time, and solved numerous econometric problems. Conditional variability is influenced by unexpected volatility, that is, the square of the residual term of the past period. The ARCH model allows variation in conditional variability at any moment. The ARCH model (q) is given by:

$$y_t \mid \psi_{t-1} \sim N(x_t \beta, h_t) \tag{2}$$

$$h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-q}, \alpha), \tag{3}$$
$$\varepsilon_t = y_t - x_t \beta,$$

where y_t stands for the time series data; ψ_{t-1} refers to all information in the period 1 to t-1; h_t represents the y_t conditional variation influenced by the residual term of the previous q; α, β are an unknown parameter; q is the order of the ARCH process; $x_t \beta$ means a linear set comprising of exogenous variables in the lagged period of the message set. In addition, the conditional residue is set to a

nonnegative value. Reorganize the equation to:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_q \varepsilon_{t-q}^2 = Z_t'\alpha, \tag{4}$$
$$Z_t' = (1, \varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \dots, \varepsilon_{t-q}^2),$$
$$\alpha = (\alpha_0, \alpha_1, \dots, \alpha_q),$$
$$\alpha_0 > 0, \alpha_i > 0, \quad i = 1, 2, \dots, q,$$

where h_t represents the current condition change related to time-varying volatility and fluctuation clustering. Based on (GARCH) model developed by Engle and Bollerslev (1986) is given the following form:

$$y_t = bx_t + \varepsilon_t,$$
$$\varepsilon_t = y_t - bx_t, \tag{5}$$
$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t),$$
$$h_t = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{j-1}^2 = a_0 + A(L)\varepsilon_t^2 + B(L)h_t^2,$$
$$q \geq 0, p \geq 0,$$
$$\alpha_0 > 0, \alpha_j > 0, j = 1, 2, \dots, q,$$
$$\beta_i > 0, i = 1, 2, \dots, p,$$

where y_t stands for the time series data, ψ_{t-1} provides all information from the period t to t-1, and h_t is the y connected with both the square of the residual q and the conditional variation from the previous period. Let the conditional variation number is the unknown parameter vector associated with the conditional average of y_t. q represents the sequence of the ARCH process, and p acts like the sequence of the GARCH process. When p=0, GARCH (p,q) will be returned. The residual term is defined as a white noise process if p=q=0 for ARCH (q).

3.3   Asymmetric Model
3.3.1   Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) Model

The EGARCH model suggested by Nelson (1991) was as follows:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left| \frac{\mu_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right| + \gamma \frac{\mu_{t-1}}{\sigma_{t-1}}, \tag{6}$$

If $\gamma < 0$ indicates the leverage effect, $\gamma \neq 0$ represents an asymmetric effect.

3.3.2   Glosten, Jagannathan and Runkle (GJR) model

The GJR-GARCH model defined by Glosten, Jagannathan, and Runkle (1993) explained the parametric form of conditional heteroskedasticity.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \, S_{t-i}^- \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{7}$$

where S_{t-i}^- represents a dummy variable that denotes the value 1 when γ_i is negative and zero otherwise.

3.3.3 Jumps Model

Concerning the jump process, this document assumes that the performance of a financial asset is part of an underlying ongoing process. The stochastic response standard is expressed as follows:

$$RJ_t(\Delta) \equiv RV_t(\Delta) - IV_t(\Delta). \tag{8}$$

This study applied stochastic volatility models to resolve the issue of impairment. The GARCH model was generally incapable of adequately explaining when it encountered excessive kurtosis in time series data.   Based on Giot and Laurent (2007), the jump-diffusion process can be evaluated by:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), 0 \le t \le T, \tag{9}$$

where dP(t) denotes the sample series' logarithmic price increment. $\mu(t)$ represents a continuous locally controlled variation, $\sigma(t)$ stands for a strictly positive stochastic volatility, $W(t)$ refers to   a standard Brownian motion, $dq(t)$ represents a counting process that equates to one for a jump to time t, and 0 if not. The jump intensity is the size of the jump for $\kappa(t)$.

Exchange rate fluctuations are expected to follow a law of probability. Jumps represent a distinct continuous-time process associated with a Poisson distribution. Assumed that X_t is the number of times and a special event like an announcement during the period [0, t]. This study used a Poisson distribution followed by X_t if:

$$\Pr(X_t = m) = \frac{l^m t^m}{m!} \exp(-lt), l > 0. \tag{10}$$

Noted that l is parameter that rules the occurrence of the special event and let $E(X_t) = l$. It had to do with the speed or intensity of the process. A continuous-time GARCH diffusion process with jumps can be stimulated as follows:

$$dp(t) = \sigma(t)dW_p(t) + \kappa(t)dq(t), \tag{11}$$

$$d\sigma^2(t) = \theta[\omega - \sigma^2(t)]dt + (2\lambda\theta)^{\frac{1}{2}}\sigma^2(t)dW_d(t), \tag{12}$$

$$\kappa(t) \sim N(0, \sigma_k^2),$$

$$dp(t) \sim \text{Poisson}(l).$$

This article provides a consistent nonparametric estimation of price variation to achieve discrete volatility. Andersen and Bollerslev (1998) used volatility to transmit continuous time. This study measured the daily volatility that is the sum of

the squared intraday returns associated with a particular trading day.

Let Δ-period return is $r_{t,\Delta} \equiv r(t,\Delta) \equiv p(t) - p(t-\Delta)$. This study normalizes the daily time interval to unity for $r_{t+1,1} = r_{t+1}$. Noted that $RV_{t+1}(\Delta)$, can be calculated as the daily volatility at the end of day t, which is stated as:

$$RV_{t+1}(\Delta) \equiv \sum_{j=1}^{1/\Delta} r_{t+j\Delta,\Delta}^2. \tag{13}$$

According to the theory of quadratic variation, when 0, the probability of no jump may be defined as:

$$RV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(i)di. \tag{14}$$

Given the quadratic variation, when $\Delta \to 0$, the probability of jumps will be converted as follows:

$$RV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(i)di + \sum_{t<i\leq t+1} k^2(i). \tag{15}$$

The realized volatility can be measured as a consistent estimator of the integrated volatility when there are no jumps while the presence of jumps occurs.

This study applies a bi-power variation measurement to split the two components of the quadratic variation process. Barndorff and Shephard (2004) illustrate that the normalized sum of the product of the absolute values of continuous returns may be used to estimate integrated volatility consistently. It is referred to as a bi-power variation (BV) and is defined as:

$$BV_{t+1}(\Delta) \equiv \mu_1^{-2} \sum_{j=2}^{1/\Delta} |r_{t+j\Delta,\Delta}||r_{t+(j-1)\Delta,\Delta}|, \tag{16}$$

where Δ represents a small value in increments time and $\mu_1 \equiv \sqrt{2/\pi} \cong 0.79788$.

The presence of jumps for $\Delta \to 0$ can be expressed as:
$$BV_{t+1}(\Delta) \to \int_t^{t+1} \sigma^2(s)ds. \tag{17}$$

The bi-power variant is meant to be robust to jumps. The product of current and lag returns makes it robust, whereas the realized variance is subject to jumps since. This paper utilizes the square of the current return. If the current or lagged return contains a jump component and another one follows the diffusion process, then the product does not affect the bi-power variation.

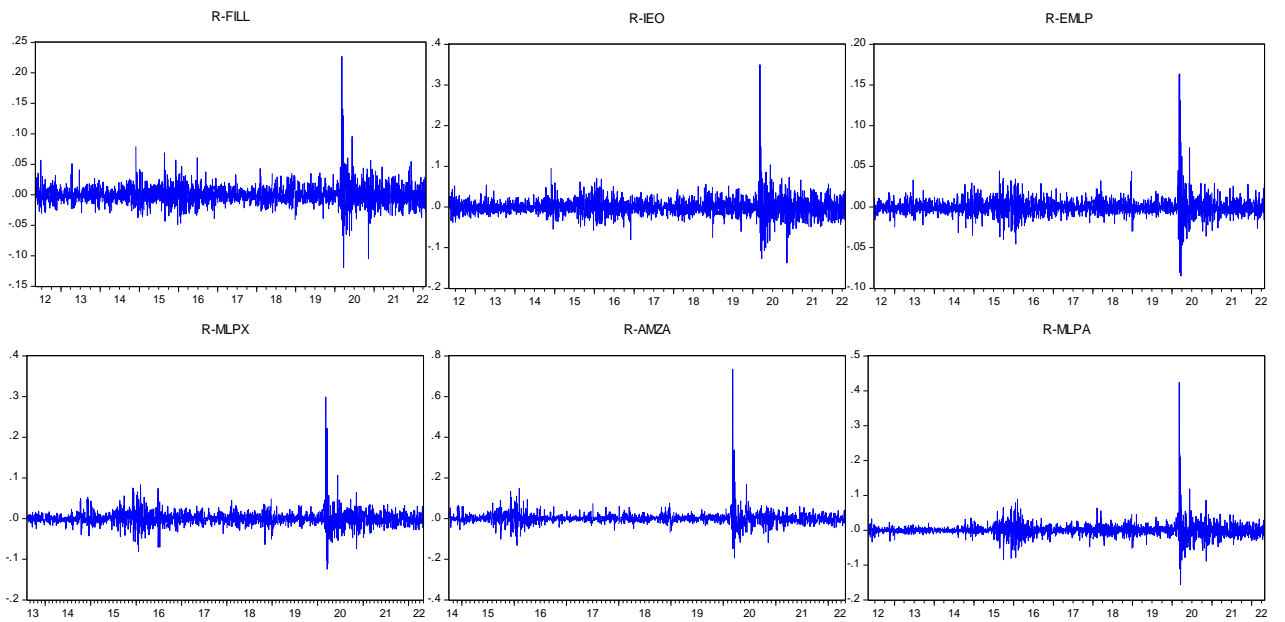## Energy ETF Returns Volatility
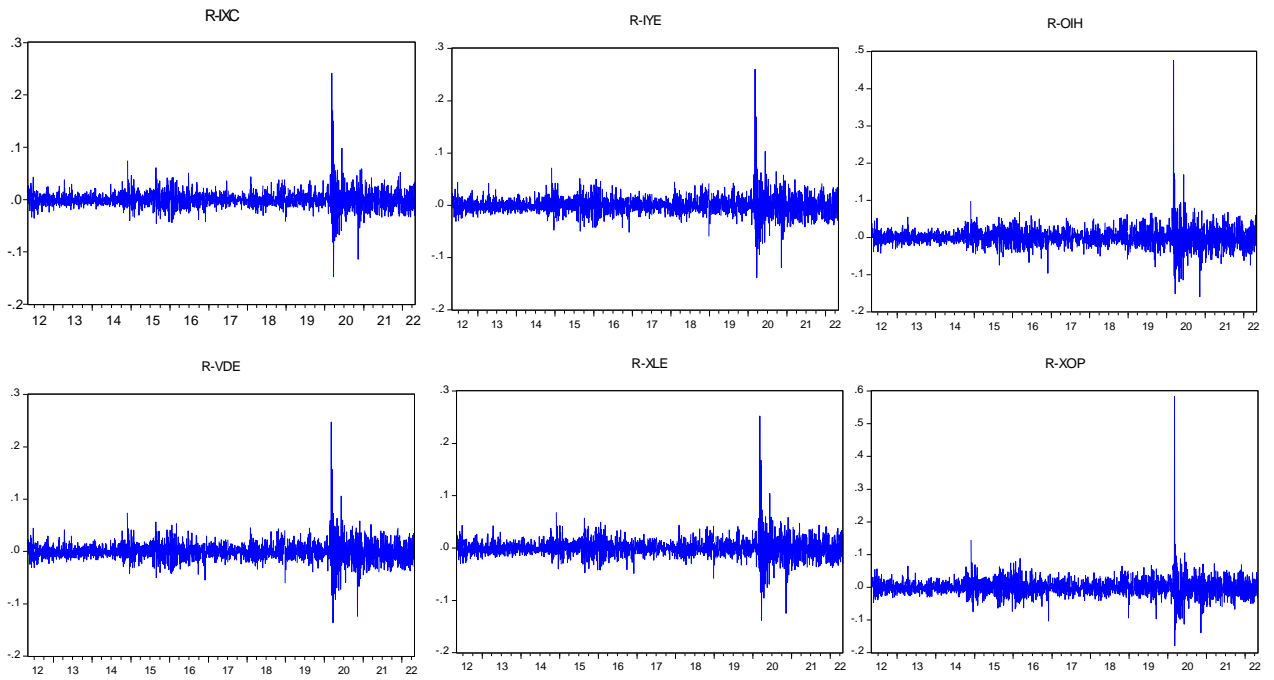
MLP ETF Returns Volatility

Figure 1: Daily Energy ETFs and MLPs ETFs market returns for clustering volatility

4. Empirical Results

Table 2 shows descriptive statistics for Energy and MLP returns. Based on the Jarque–beta test, all significant test results demonstrated non-Gaussian properties of the return series in both ETFs. With a considerable positive kurtosis over 3, Energy and MLP ETFs have a modest positive bias and are leptokurtic or "fat-tailed." The daily return distribution is higher-peaked than a normal distribution, indicating that the GARCH effect is evident in both ETFs. All Energy ETFs and MLP ETFs show positive average returns except for MLPs ETFs for EMLP (-0.0849). In the case mean return, the (XOP) ETF in Energy and the (AMZA) ETF in MLPs have the highest volatility (0.02703) and (0.0325), respectively. Table 3 represents the ARMA-GARCH, LM, ARCH-LM, and Augmented Dickey-Fuller test results.

Table 2: Descriptive statistics of Energy and MLP ETFs

	IXC	IYE	OIH	VDE	XLE	XOP
Energy ETF						
Mean	0.000182	0.000178	0.000781	0.000164	0.000146	0.000566
St. Div.	0.016754	0.018140	0.026021	0.018207	0.018089	0.027037
Minimum	0.241491	-0.13858	-0.15920	-0.13593	-0.13820	-0.17925
Maximum	-0.14760	0.260405	0.475904	0.247278	0.252210	0.584049
Skewness	1.868314	1.591119	2.518143	1.351387	1.561385	3.880399
Kurtosis	33.79879	29.03935	51.17401	24.92739	28.33053	90.98395
J-Bera	1009.0***	721.61***	2459.4***	511.75***	682.12***	817.3***
	IEO	FILL	AMZA	EMLP	MLPA	MLPX
MLPs ETF						
Mean	0.0001	0.0001	0.0015	-0.0849	0.0005	0.0002
St. Div.	0.0218	0.0162	0.0325	0.011625	0.01992	0.0192
Minimum	-0.1378	-0.1195	-0.1941	-0.0849	-0.1562	-0.1245
Maximum	0.3498	0.2268	0.7354	0.16371	0.42448	0.2989
Skewness	1.7877	1.5498	7.0144	3.0535	4.7908	3.0214
Kurtosis	33.4345	25.6065	145.74	43.972	96.798	44.033
J-Bera	98443.57***	54517.9***	1.703***	2.036***	9.918***	1.8091

Note: *, ** and *** denote at 10%, 5% and 1% significant level respectively for both energy and MLP ETFs.

ADF test for Energy and MLP ETFs returns. At the 1% significance level, the daily return series shows significant ARCH effects at 1 to 4 lags periods. The trend of the returns series in Figure 1 shows that significant price volatilities are followed by massive movements confirming these findings. Also, ADF tests are used before adjusting time series to check for stationarity. The null hypothesis of unit root is intensely rejected by the Augmented Dickey-Fuller (ADF) test, which shows evidence of stationary in the time series dataset. Using the Akaike Information

Criterion (AIC) minimum value, this article compares many alternative models and finds the most suitable one for the data. In addition to verifying the serial correlation of the problem, the Breusch–Godfrey Lagrange multiplier test was used, and the results show no serial correlation in both ETF returns. The Lagrange Multiplication (ARCH-LM) test was used in this study to diagnose the ARCH effect. Using the best order of ARMA statistics, this article rejected the null hypothesis of no ARCH effect and significantly accepted the alternative hypothesis of the ARCH effect for the two ETFs. The ARCH-LM test is also used to properly evaluate the hypothesis that the residuals of the GARCH-ARMA and EGARCH-ARMA models include ARCH errors. The test results show no autoregressive conditional heteroscedasticity in both Energy and MLPs ETFs.

Table 3: ARMA- GARCH, LM, ARCH-LM, and ADF test for Energy and MLP ETFs

	Energy ETFs					
	IXC	**IYE**	**OIH**	**VDE**	**XLE**	**XOP**
ADF	-20.607***	-20.970***	-32.640***	-20.773***	-20.922***	-52.840***
ARMA	(0,2)	(0,2)	(1,1)	(0,2)	(0,2)	(2,2)
AIC	-5.3462	-5.1873	-4.4636	-5.1782	-5.1922	-4.3894
LM	**0.4811**	**0.1628**	**4.4049**	**0.1504**	**0.2158**	**3.8572**
	(0.7862)	**(0.9218)**	**(0.110)**	**(0.927)**	**(0.897)**	**(0.1453)**
ARCH-LM	**48.053*****	**308.712*****	**90.208*****	**358.776*****	**137.545*****	**42.1065*****
	(0.0000)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
GARCH	(1,1)	(1,2)	(1,2)	(2,2)	(2,2)	(1,2)
AIC	-5.8382	-5.6601	-4.9325	-5.6428	-5.7010	-4.7774
ARCH-LM	**0.0246**	**0.6627**	**1.1485**	**0.7228**	**0.2702**	**0.1939**
	(0.9999)	**(0.9558)**	**(0.8865)**	**(0.9485)**	**(0.8736)**	**(0.9076)**
	MLPs ETF					
	IEO	**FILL**	**AMZA**	**EMLP**	**MLPA**	**MLPX**
ADF	-20.903***	-21.116***	-16.752***	-19.880***	-19.739***	-18.465***
ARMA	(2,1)	(0,2)	(2,2)	(1,2)	(2,2)	(1,2)
AIC	-4.8149	-5.4095	-4.0245	-6.0835	-5.003	-5.0619
LM	**1.1776*****	**1.7724**	**1.002**	**1.4089**	**1.0581**	**0.1508**
	(0.555)	**(0.4122)**	**(0.606)**	**(0.4944)**	**(0.5892)**	**(0.9274)**
ARCH-LM	**54.682*****	**121.848*****	**38.525*****	**690.390*****	**177.682*****	**438.611*****
	(0.0000)	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**	**(0.0000)**
GARCH	(2,2)	(2,2)	(1,2)	(2,2)	(1,2)	(2,2)
AIC	-5.2129	-5.7481	-4.8964	-6.7194	-5.9661	-5.7063
ARCH-LM	**0.3359**	**0.0409**	**0.1460**	**1.6213**	**1.1603**	**0.8814**
	(0.8454)	**(0.8397)**	**(0.9297)**	**(0.8050)**	**(0.8846)**	**(0.9272)**

Note: *, ** and *** denote at 10%, 5% and 1% significant level respectively for both energy and MLP ETFs.

4.1 Symmetric models for ARMA-GARCH

One of the well-known phenomena in financial economics is the leverage effect. Black (1976) explored the historical association between equity returns and volatility changes. When bad news happens on the market, the volatility of the corresponding value usually increases due to unpredictable future developments. Negative news affected prices resulting in a negative return. The estimations result of the ARMA-GARCH model is reported in Table 4. When the value of α+β is equal to or less than 1 when added together indicates the influence of GARCH order. Chen and Hung (2010) also illustrate how different order levels interact with GARCH variations. The majority of instant criteria represent findings close to or equal to 1 that guarantee the possibility of the near-maximum likelihood estimator for the GARCH model.

Table 4: ARMA-GARCH Assessments for Energy and MLPs ETFs.

Energy ETFs						
ETF	IXC	IYE	OIH	VDE	XLE	XOP
ARMA/ GARCH	(0,2)/ (1,1)	(0,2)/ (1,2)	(1,1)/ (1,2)	(0,2)/ (2,2)	(0,2)/ (2,2)	(2,2)/ (1,2)
α+β	0.9955	0.9952	1.0000	0.9999	0.9998	0.9990
MLPs ETF						
ETF	IEO	FILL	AMZA	EMLP	MLPA	MLPX
ARMA/ GARCH	(2,1)/ (2,2)	(0,2)/ (2,2)	(2,2)/ (1,2)	(1,2)/ (2,2)	(2,2)/ (1,2)	(1,2)/ (2,2)
α+β	0.9982	0.9779	1.0039	0.9931	1.0163	0.9933

These result report that the volatility rate of both Energy and MLPs ETFs are highly persistent and vary highly in the time series. Radha and Thenmozhi (2006) predicted short-term interest rates and found that the GARCH model was more predictive than other models because of the volatility of clusters.

4.2 Asymmetric model for ARMA-EGARCH, ARMA-GJR, and Jump Model
4.1.1 ARMA-EGARCH Model Results

This study uses the EGARCH, GJR-GARCH, and Jump models to assess the volatility leverage effect of the two ETFs. Results from the EGARCH-ARMA model provided evidence for leverage. In Table 5, all the coefficients of (γ) reported at a 1% significance level and confirmed leverage exists in both ETFs. The leverage term (γ) positively influences the conditional variance of ETF market returns. The results show a large positive symmetric or inverse leverage effect in the Energy and MLPs ETFs, which is consistent with the study of Benth and Vos (2013), Bowden and Payne (2008), and Suleman (2012). Bowden and Payne (2008) found that the most important impact on volatility returns appeared to be the positive impact on electricity prices. Suleman (2012) found that the impact of negative news outweighed positive news.

Table 5: ARMA-EGARCH results for Energy and MLPs ETFs

Energy ETFs						
ETF	IXC	IYE	OIH	VDE	XLE	XOP
ARMA/ EGARCH	(0,2)/ (1,1)	(0,2)/ (1,1)	(1,1)/ (1,2)	(0,2)/ (1,1)	(0,2)/ (2,1)	(2,2)/ (1,2)
γ	**0.0758*** (0.0000)**	**0.0670*** (0.0000)**	**0.0611*** (0.0000)**	**0.0682*** (0.0000)**	**0.0882*** (0.0000)**	**0.0775*** (0.0000)**
MLPs ETF						
ETF	IEO	FILL	AMZA	EMLP	MLPA	MLPX
ARMA/ EGARCH	(2,1)/ (1,1)	(0,2)/ (1,2)	(2,2)/ (2,1)	(1,2)/ (2,1)	(2,2)/ (1,2)	(1,2)/ (2,2)
γ	**0.0731*** (0.0000)**	**0.0708*** (0.0000)**	**0.1193*** (0.0000)**	**0.1225*** (0.0000)**	**0.1141*** (0.0000)**	**0.0167*** (0.0000)**

Note: *, ** and *** denote at 10%, 5% and 1% significant level respectively for both Energy and MLPs ETFs.

4.1.2 GJR-GARCH model results

Glosten et al. (1993) created the GJR-GARCH model and used it to simulate the asymmetry process of the GARCH. For ARIMA-GARCH nonlinear modeling, this article uses AIC criteria to find the best ARMA order by choosing from different models. Models with smaller AIC values are commonly used to select the ARMA order. This paper uses the GJR model to evaluate whether there is a leverage effect. The GJR-GARCH model results are presented in Table 6. Results confirmed the conditions of the GJR model. All coefficients must be significant for conditions, such as $\omega \geq 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \gamma_1 \geq 0$, when there is a positive shock: $\varepsilon_{t-1} > 0$ and for negative shocks: $\varepsilon_{t-1} < 0$, while β_1 reflect the good news in relation with $\alpha_1 + \gamma_1$, so $\gamma_1 > 0$ represent that there will be a negative effect leading to higher volatility. The asymmetry coefficient for the GJR model, all (α_1) and (β_1), are found to be positive and significant at the 1 % level. These results indicated that volatility of both Energy and MLPs ETTs returns have enhanced.

Table 6: GJR-GARCH statistics of Energy and MLP ETFs

Energy ETFs						
ETFs	IXC	IYE	OIH	VDE	XLE	XOP
ARMA/GARCH	(0,2)/ (1,1)	(0,2)/ (1,2)	(1,1)/ (1,2)	(0,2)/ (2,2)	(0,2)/ (2,2)	(2,2)/(1,2)
ω	0.0258**	0.0192***	0.0102*	0.0023***	0.0045	0.0368*
	(0.0126)	(0.0096)	(0.0822)	(0.0000)	(0.3958)	(0.0172)
α_1	0.1348***	0.2135*	0.2796*	0.2009***	0.2360*	0.3387*
	(0.0021)	(0.0300)	(0.0131)	(0.0000)	(0.0212)	(0.0423)
β_1	0.9028***	0.9318***	0.9627***	1.6855***	1.5459***	0.9406***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	-0.093***	-0.203*	-0.2559*	-0.202***	-0.238*	-0.3379*
	(0.0079)	(0.0347)	(0.0195)	(0.0000)	(0.0228)	(0.0399)
$\alpha + \beta + \left(\frac{\gamma}{2}\right)$	**0.9908**	**0.9931**	**0.9989**	1.7852	**0.9982**	**0.9961**
MLPs ETFs						
ETFs	IEO	FILL	AMZA	EMLP	MLPA	MLPX
ARMA/GARCH	(2,1)/ (2,2)	(0,2)/ (2,2)	(2,2)/ (1,2)	(1,2)/ (2,2)	(2,2)/ (1,2)	(1,2)/ (2,2)
ω	0.0108*	0.0154*	0.0840*	0.0065*	0.0067*	0.0040***
	(0.0755)	(0.0259)	(0.0840)	(0.0451)	(0.0131)	(0.0000)
α_1	0.2482*	0.1646*	0.6059*	0.2785***	0.4859**	0.2977***
	(0.0149)	(0.0275)	(0.0198)	(0.0000)	(0.0030)	(0.0000)
β_1	1.4098***	1.3183***	0.8859***	1.5057***	0.9193***	1.6864***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ_1	-0.2604*	-0.1658*	-0.5209*	-0.213***	-0.421***	-0.329***
	(0.0101)	(0.0253)	(0.0356)	(0.0006)	(0.0080)	(0.0000)
$\alpha + \beta + \left(\frac{\gamma}{2}\right)$	**0.99746**	**0.9935**	**0.9956**	**0.9923**	**1.0005**	**0.8272**

Note: *, ** and *** denote at 10%, 5% and 1% significant level respectively for both energy and MLP ETFs.

The results of Energy and MLPs ETFs findings reported that the majority of cases had a strong negative significant effect at the 1 % level. In addition, the leverage term (γ1) negatively impacts the conditional variance of ETF market returns. It shows a strong asymmetric impact of leverage on all ETFs returns. The second phase requirements concern $\alpha+\beta+\gamma_2<1$, and it fulfills the condition that all results of both Energy and MLPs ETFs are close to 1. These results supported Chen and Tung's (2019) and Bunnag's (2014) research.

4.1.3   Jump detection

This section provides the results obtained using the Bi-Power Variations method. The study examined the distinction between performed volatility (VR) and performed jump, also known as bi-power variation (BV). If a jump effect exists, it is asymmetrical. Table 7 shows the jump model estimations. There is evidence of steady jump intensity in the data. This paper provides a new nonparametric test for spotting Energy and MLPs ETFs returns jump arrival times and realized jump frequency on daily closes price data. This paper examines the difference between realized volatility (VR) and two-power variation (BV). If the jump occurs, the ETF has an asymmetric impact (Chen and Tung, 2019). The estimates for the average frequencies show that an average jump is positive for both ETFs. Based on the selected observation on Energy ETFs, we found XLE and VDE have a higher number of detected jumps (25) with a critical value of 3.090, and the jump percentage becomes 24.03% of total data. For MLPs, MLPX shows the maximum number of detected jumps (53) with a critical value of 3.090, which is the highest variable among both Energy and MLPs ETFs in terms of jump detection.

The empirical results reveal that both Energy and MLPs have a jump effect, while MLPs ETFs reported the highest frequency of Jumps with an average percentage of 24.79%. In Table 7, the presence of jumps and their significant influence may give knowledge to the investors, with a correct investing tool for decision making of future trading planning and investment.

Bi-power Variation (BV) and Realized Jumps (RJ) variations of Energy and MLPs ETF as shown in Figures 2 and 3. The figures exhibit integrated volatility and Bi-Power variation for the continuous GARCH jump process for Energy and MLPs ETFs. Unlike return volatility RVT (Δ), this study revealed that the Bi-Power volatility is a much better estimate of the integrated volatility in the presence of jumps. The Bi-Power Variations is built for robust jumps because its basic structure is the product of two continuous returns rather than just the squared return. Figures show that each ETF displays apparent jump fluctuations, indicating an asymmetric effect. These results align with those of Liao, Lin, and Liao (2017).

Table 7: Realize Jump (RJ) statistics of Energy and MLPs ETFs

Energy ETFs						
ETFs Code	**IXC**	**IYE**	**OIH**	**VDE**	**XLE**	**XOP**
Number of detected jumps	17	24	21	25	25	15
Expected number of spurious detected jumps	0.104	0.104	0.104	0.104	0.104	0.104
Proportion of detected jumps	0.1634	0.231	0.200	0.240	0.240	0.144
Critical level:	0.001	0.001	0.001	0.001	0.001	0.001
Critical value:	3.090	3.090	3.090	3.090	3.090	3.090
Observations	104	104	104	104	104	104
Jump Ratio	0.16	0.23	0.20	0.24	0.24	0.14
Jump Percentage	16.34%	23.07%	20.19%	24.03%	24.03%	14.42%
Jump Average Percentage	**20.35%**					
MLPs ETFs						
ETFs Code	IEO	FILL	AMZA	EMLP	MLPA	MLPX
Number of detected jumps	24	19	31	13	30	53
Expected number of spurious detected jumps	0.104	0.101	0.299	0.068	0.104	0.188
Proportion of detected jumps	0.23076	0.1881	0.3344	0.1911	0.2884	0.2819
Critical level:	0.001	0.001	0.001	0.001	0.001	0.001
Critical value:	3.090	3.090	3.090	3.090	3.090	3.090
Observations	104	101	101	68	104	188
Jump Ratio	0.10	0.10	0.29	0.06	0.10	0.18
Jump Percentage	23.07%	18.81%	30.69%	19.11%	28.84%	28.19%
Jump Average Percentage	**24.79%**					
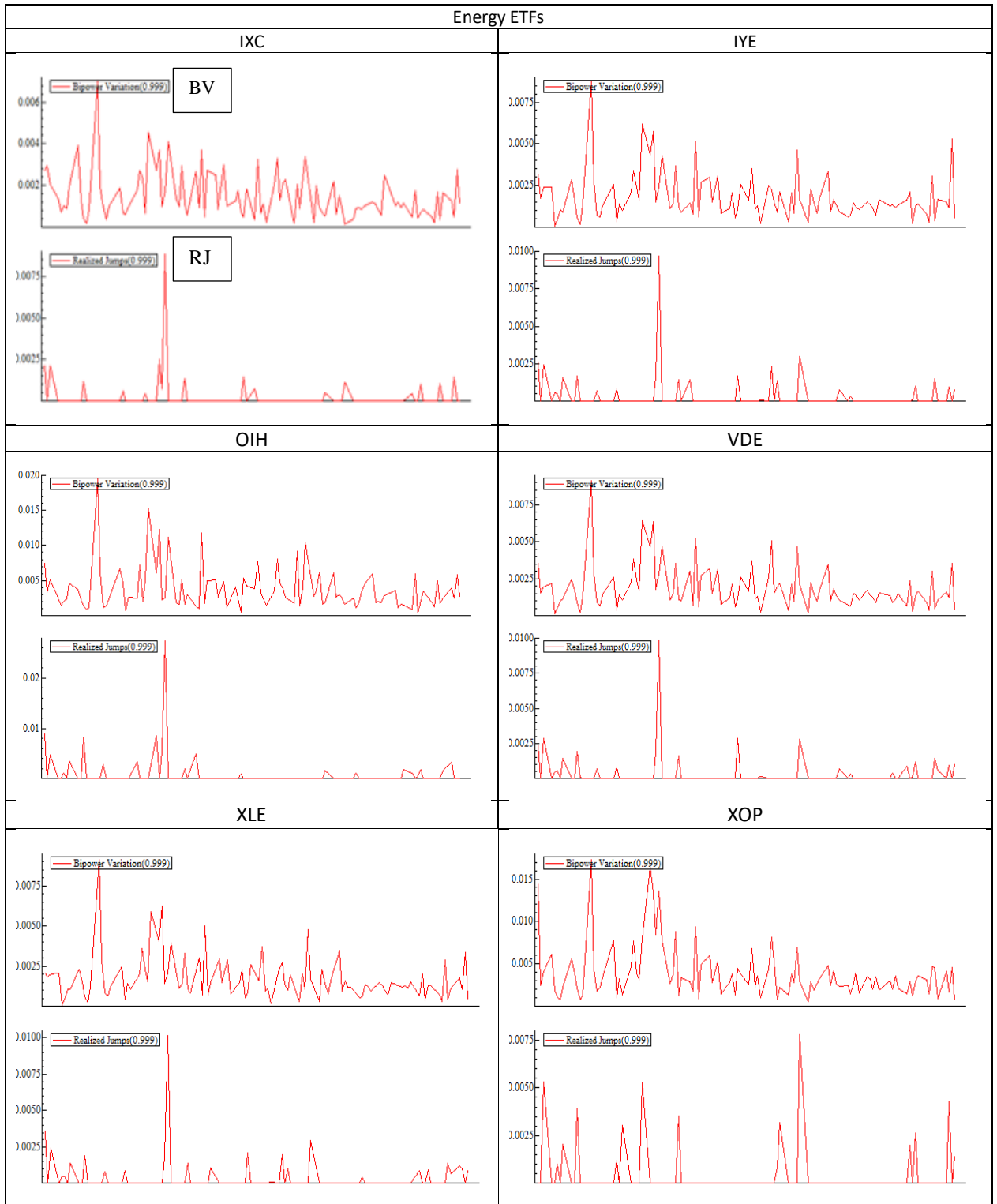
Figure 2: Bi-power Variation (BV) and Realized Jumps (RJ) of variations of Energy ETFs
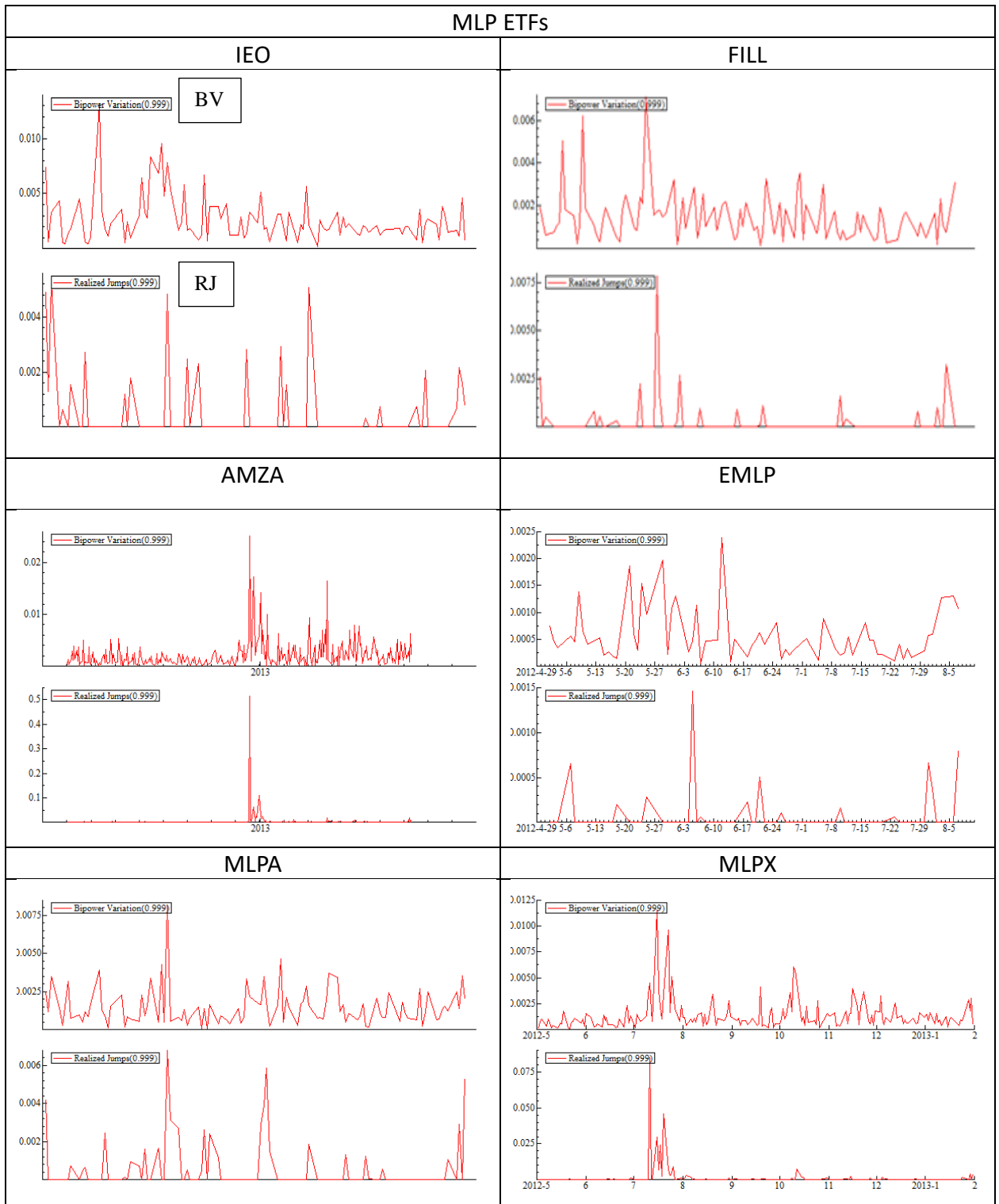
Figure 3: Bi-power Variation (BV) and Realized Jumps (RJ) of variations of MLP ETFs

5. Conclusion

paper examines the impact of price volatilities on Energy and Master limited partnership ETFs traded in the United States using the ARMA-GARCH, ARMA-EGARCH, and the GJR-GARCH models. Empirical research on the asymmetric effect of ETF Energy and MLP is covered in this paper. The study was driven by the gap and explored the impact of ETFs on investment decisions and risk. The study contributes basic information about the frequency of jumps in daily ETFs market returns and discovers high volatility in conditional jumps and the jump size distribution.

This study looks at the volatility dynamics by daily information. The ARMA model is first used to select the order which best corresponds to the ARCH effect, then to estimate the GARCH model. The price volatilities of ETFs are separated into two categories Energy and MLPs. The empirical results of ARMA-EGARCH revealed that the effect of positive news was greater in both groups than the influence of negative news. The leverage term (γ) positively influences the conditional spread in ETF market returns. The results generally show a significant positive symmetric or inverse leverage effect in Energy and MLPs ETF.

The GJR GARCH result meets the requirement that the volatilities generated by the unintentional negative shock were bigger than the fluctuation stimulated by the predicted shock to enhance prediction performance. The asymmetry coefficient for the GJR model, all ($\alpha 1$) and ($\beta 1$), is positive and significant. These results indicated that highly volatile for both Energy and MLPs ETTs returns. Both Energy and MLP ETFs returns are asymmetric.

Finally, the Jump effect fills the variance of conditional volatilities, demonstrating that volatilities are discontinuous. This study revealed that The Bi-Power volatility BV t (Δ) is a much better estimate of the integrated volatility in the presence of jumps. The MLPs ETFs performed well in terms of Jump effects. The presence of jumps and their significant influence can provide investors with a proper investment tool for decision-making, future planning, and investment. It is beneficial for policymakers and market players to appropriately respond to global energy price shocks and reduce the price volatility of Energy and MLP ETFs.

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