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Energy ETF return jump contagion: a multivariate Hawkes process approach

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ABSTRACT
Compared with investing in individual stocks, ETF investment is capable of diversifying the non-systematic risk or exposure to broad market or industry sectors.The aim of thispaper isto developa jumpcontagion modeling framework to understand the contagion effect of market jump events of energy sector ETFs using multivariate Hawkes process modeling approach.Through analyzing intraday high-frequency market data, wefind that negative index jumps lead index pricediscovery processes, and their influencesdisappear faster than the positive index jumpsin both the S&PSOO and the crude oil futures. And on average, the self contagion in negative jumps is stronger than the self contagion in the positive jumps across all ETF groups. However, the ETFs focused on the master limited partnership (MLP) segment show less negative self contagion and relatively stronger positive self contagion than the other energy ETFs. Overall, the influence of negative jumps on ETFs from both the equity index and the energy future index isstronger than that of the positive jumps. And the influence of the equity index (S&PSOO) jump on ETFs lasts longer than that of the crude oil futures index (CLC1).

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Energy finance; energy ITFs; crude oil futures; multivariate Hawkes process; price discovery

1. Introduction

Energy economy has attracted attention from researchers for more than a century as our modern life relies on affordable and adequate supply of energy. In particular, the price movement of crude oil has been attributed to market recessions, periods of excessive inflation, reduced productivity and lower economic growth. With its significant impact on the financial market, shocks of price action within the energy market would be of major concerns for investors and regulators. In this paper, we aim to investigate the shock transmission effect on one of the most popular energy investment vehicles: Exchange Traded Funds (ETFs).

Empirical studies have suggested a strong linkage between energy crude oil prices and macroeconomic conditions (Hamilton 2003; Barsky and Kilian 2004; Du, Yanan, and Wei 2010; Acaravci, Ozturk, and Yilmaz Kandir 2012; Ordu and Soyta 2016). On the one hand, the surge of energy prices contributes to higher input cost for firms, which leads to declining profits and collectively affects the macroeconomic conditions. On the other hand, rising energy prices increase cost-push inflationary pressure and lead to an increase in nominal interest rate (Sadorsky 1999). Subsequently, such an increase in energy prices leads to higher financing cost for enterprises and negatively affects the financial markets. Macroeconomic conditions also play a significant role in crude oil prices in different states of the business cycle. During the prosperity phase, the economy is at its peak of the trade cycle with strong consumption and productivity leading to an increased demand for energy; during the depression phase, the economy experiences a significant decline in economic activities leading to a decreased demand for energy.

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In recent years, index ETFs, which track the performance of specific benchmark indices byholding a diversified setof assets such asstocks, commodities, or bonds, have become attractive investment options for investors. In contrast to individual stock picking, investing in ETFs diversifies the non-systematic risk and exposure to market indices and industry sectors. ETFs typically collect lower management fees, exhibit a higher degree of transparency and flexibility when compared to traditional mutual funds. As a result, ETFs have become an important source of information dissemination in the financial market. Specifically within the energy sector, crude oil is one of the world's most important commodities serving as a major energy source for economic development. The volatility of crude oil futures hasa material impact on the global economy and financial marketstability (Wang etal. 2016; Amelieand Dame 2017;Gong and Lin 2018).Therefore, it isespecially important for investors and risk managers to understand the empirical spillover effects of jump events relating to major energy ETF instruments.

When price interaction among multiple markets is analyzed in the context of returns, testing of spillover effects is mostly based on the well-known Granger (non-) causality test in a vector autoregressive process (Eun and Shim 1989; Hamao, Masulis, and Ng1990; Forbes and Rigobon 2002). Forbes and Rigobon (2001) define contagion as a significant increase in cross-market linkages after a shock to one country (or groupof countries). Thisdefinition specifically refers to contagion effect if the cross-market comovement increasessignificantly after the shock. A number of studies have examined the shock transmission mechanism across different markets. Kaminsky and Reinhart {1998); Baig and Goldfajn (1999); Dornbusch, Chul Park, and Claessens (2000); Ang and Chen (2002); Bae, Andrew Karolyi, and Stulz (2003); Tang and Xiong (2012). The transmission of shocks has been measured by either simple cross-market correlation coefficients or probit models. A second approach to test for contagion is to use an ARCH (Engle 1982) or GARCH (Bollerslev 1986) framework to estimate the variance-covariance transmission mechanism across countries. Some popular specifications include the multivariate extension of the model proposed by McAleer, Hoti, and Chan (2009), the matrix-exponential GARCH (Kawakatsu 2006), or the asymmetric BabaEngleKraftKroner (BEKK) model (Engle and Kroner 1995; Kroner and Ng 1998). Spillover effects can also be tested in terms of the conditional volatility. Modelling and testing spillovers between the energy and agricultural markets have typically been based on estimating multivariate conditional volatility models, specifically the BEKK model of Engle and Kroner (1995) and the DCC model of Engle (2002). However, Chang, McAleer, and Wang (2018a, 2018b) conduct an in-depth literature review pointing to the incorrect applications of the full BEKK and DCC models for testing volatility spillover effects. Nevertheless, we argue that major shocks are rare events, and the existing methods of testing spillover or contagion tend to adapt to normal and near-normal conditions. Unusual and extreme market events tend to have much more substantial net impacts despite occurring a much smaller proportion of the time. One of the major contributions of this study is to offer a different framework to study the contagion effect of these unusual market events using a multivariate Hawkes process framework.

This research focuses on 'tail' market events and aims to understand the shock transmission mechanism between financial market and major typesofenergy ETFs using multivariate Hawkes process approach. Hawkes process model was first introduced by A.G Hawkes in the 1970s (Hawkes 1971) and more recently it has been widelyapplied in variousstudies relatedto the financial markets (Bacry,Mastromatteo, and Muzy 2015). Hawkes process model seeks to explain how the occurrence of an event will increase or decrease the probability of future occurrences of the same event or other events. In financial applications, it captures the contagion effect of jump events that can be observed in asset price movements. Risk, especially involving large swings of price movement, is a primary concern for investors and risk managers. As a result, return jump events are of great interest to researchers and market practitioners. Unlike traditional regression or linear timeseries models, the multivariate Hawkes processes do not require that the underlying time series data arestationary. Instead, it takes account of the occurrences of large market jump events. In this research, we collect historical time series price data of the S&P 500 index, crude oil futures and the 24largest energy ETFs byasset under management and build multivariate Hawkes process models of large shock events. By analyzing the model parameters, we aim to uncover the directions ofinformation flow and explain the pricediscovery process between financial market and energy ETFs. From an investment perspective, such knowledge would facilitate the decision-making process on constructing optimal portfolios and hedging the volatility of the energy sector. From a regulatory perspective, the empirical insights should help understand the potential risk propagation mechanism between the overall financial market and the energy sector. Specifically, we divide the 24 energy ETFs into three distinct groups on the basisof their operations i.e. equity[1], master limited partnership (MLP)[2], and infrastructure[3]. The main purpose of the study is to investigate the empirical mechanisms of large jump events in these energy ETFs and financial market, namely their rollover, cross-excitation, and time-decaying effects.

Overall, we find that energy ETFs share some common attributes with other ETFs that return jumps are highly correlated with the U.S. equity market. The market index jumps consistently lead ETF jumps in both positive and negative directions. In other words, major market indices, i.e. S&P500 and crude oil futures, lead the price discovery process in both positive and negative directions. We find that negative index jumps lead index price discovery processes, and their influences disappear faster than the positive index jumps. And on average, the self contagion in negative jumps is stronger than the self contagion in the positive jumps across all ETF groups. However, the ETFs focused on the master limited partnership (MLP) segment show less negative self contagion and relatively stronger positive self contagion than the other energy ETFs. Overall, the influence of negative jumps on ETFs from both the equity index (S&P500) and the energy future index (CLCl) isstronger than the influence of the positive jumps. And the influence of the equity index jump on ETFs lasts longer than that of energy future index. To the best of our knowledge, this research is the first study to focus on analyzing jump events within the energy sector and document the directional jump transmission from financial market to energy ETFs.

The rest of the paper is organized as follows. In Section 2, we conduct a literature review on the state of energy finance and ETFs, along with their empirical relations with the U.Sequity market. In Section 3, we detail the data collection process and present the methodologies of the bipower variation jump identification and the multivariate Hawkes process. In Section 4, wediscuss various jump effects along with their implications from the parameter calibration process. In the last section, we condude the findings of our study with key contributions.

2. Literature review

Economists have long been intrigued by empirical evidence that oil price shocks may be closely related to macroeconomic performance, but the answer has never been straightforward (Rotemberg and Woodford 1996; Barsky and Kilian 2004).It has become widely accepted in recent years that the priceof crude oil since the 1970s has responded to some of the same economic forces that drive stock prices, making it necessary to control for reverse causality (Hamilton 2003; Hammes and Wills 2005; Kilian 2008). The instability of regressions based on oil prices and, in particular, why higher oil prices seem to matter less today than in the 1970s and early 1980s (Kilian 2009). Kilian and Park (2009) document that the demand and supply shocks driving the global crude oil market jointly account for 22% of the long-run variation in U.S. real stock returns. The responses of industry-specific U.S. stock returns to demand and supply shocks in the crude oil market are consistent with accounts of the transmission of oil price shocks that emphasize the reduction in domestic final demand.

More recently, Benkraiem et al. (2018) show the impact of energy price shocks on financial market prices by analyzing the relationship between S&P 500 Index and energy prices that include WTI, gasoline, heating, diesel and natural gas prices. Based on the Quantile Autoregressive Distributed Lags (QARDL) model, the empirical results infer that crude oil and natural gas are key economic variables to explain short-run and long-run stock market dynamics. In another study, Bastianin and Manera (2018) reveal the response of the U.S. stock market volatility to three differentstructural oil market shocks basedon a structural Vector Autoregressive model. Their results show thatstock market volatility responds significantly to oil price shocks caused byunexpected changes in aggregate and oil-specific demand, but it is negligible to supply-side shocks. It has important implications for policy makers, investors, risk managers and so on. Kang, Perez de Gracia, and Ratti (2017) analyze the impact of oil priceshocks and economic policy uncertainty on the stock returns ofoil and gas companies usinga structural vector autoregressive model. The empirical results show that oil demand-side shocks have positive effects on the return of oil and gas companies, while policy uncertainty shocks have negative effects on the return. And there are heterogeneous effects of structural shocks on upstream, midstream and downstream oil and gascompanies. Shi and Sun (2017) investigate the relationship between the regulatory price distortion and economic growth using a two-sector growth model. In contrast to the intuition that the regulatory price distortion helps mitigate the negative impact of price volatility from oil imports and have a positive effect on the economy, the empirical results reveal that the regulatory pricedistortion has negative effects on output growth in China both in the short term and long term. It suggests a market-oriented energy price regime to improve the economic growth. The free cash flow (FCF) hypothesis is very famous in the energy corporate finance and it is first raised by Jenson (Jensen 1986). Shi (2019) investigates the sensitivity between free cash flow and over investment in China's energy companies using Richardson (Richardson 2006) investment expectation model. Then he checks how the corporate governance mechanisms impact the sensitivity between free cash flow and over investment. The empirical results show free cash flow will positively impact overall investment.

From the investors' perspective, it is well known that ETFs facilitate to reduce the non-systematic risk and have become an important source of information dissemination in the financial market. Given the growing popularity of the energy ETF investment, energy EFTs have attracted scholars' interest in the energy finance field in recent years. Chang, McAleer, and Wang (2018a) analyze the spillover effects within and across the U.S. energy and financial sectors using generated regressors and a multivariate conditional volatility model. The empirical results show a significant relationship between the financial ETF and energy ETF in the spot and futures markets. It implies that there is an optimal portfolio to hedge the risks in financial markets. Chang, Liu, and McAleer (2019) investigate the interaction and co-volatility spillovers between the energy and agricultural industries using multivariate conditional volatilitydiagonal BEKK models. The empirical results can be used to design hedgingstrategies between the energy and agricultural industries, especially between bio-ethanol and bio-ethanol-related agricultural commodities. Alexopoulos (2018) investigates the performance of energy ETFs using different investment strategies, under market turmoil and market uptrend periods. The empirical results show the portfolio performance of all ETFs in aggregate outperform two disaggregated portfolios with dean and conventional ETFs separately. Chang and Ke (2014) investigate the relationships between returns and flows of five ETFs in the U.S. energy sector, using a Vector Autoregressive (VAR) model. In the study, they test four hypotheses including price pressure hypothesis, information hypothesis, feedback trading hypothesis and smoothing hypothesis. The empirical results support the smoothing hypothesis but do not support the price pressure hypothesis, information hypothesis or feedback trading hypothesis. Krause and Tse (2013) examine the price discovery and volatility spillovers between Canadian and U.S. equity markets through Granger-causality tests and bivariate EGARCH models. The empirical results show that there is a significant lead-lag relationship in returns from U.S. market to the Canadian market, but no opposite direction. While there is a bi-directional volatility spillovers between the U.S. market and the Canadian market.

3. Methodology and data

In thissection, we first describe a methodology to identify jump events in different markets. Here we focus on significant return jump events rather than thecontinuous returnseries. Wethen discussthe multivariate Hawkes process model. Our goal is to use Hawkes process model to explain the complex interactions of different types of market events.

3.1. Bipower variation jump identificationmethod

We apply the bipower variation jump identification method (Barndorff-Nielsen and Shephard 2006) to identify whether there are jump events in the non-overlapping 5-minute return series of the S&P 500 index, crude oil futures and energy ETFs. We define the discretized version of y^* as

$$y^*_\delta(t) = y^*(\delta\lfloor t\delta^{-1}\rfloor), \quad t \geq 0, \tag{1}$$

where 8 is the 5-minute grid size of the time interval; $Lx J$ is the integer part of x. Then we construct 8-returns as

$$Jj = y^*(j8) - y^*((j-1)8), \quad j = 1,2,\ldots, Lt/8J. \tag{2}$$

where Jj is the valueof log return in this 5-minute interval.

We define $Y^*(t)$ as log price of the asset, and δ is the 5-minute grid size of the time interval. And then $[y^*_\delta]_i$ is the realized quadratic variations (QV) process, and it is defined as:

$$[y^*_\delta]_i = [y^*_\delta](h(i)) - [y^*_\delta](h(i-1)), \quad i = 1,2,\ldots,T,$$
$$= \sum_{j=1}^{\lfloor t/\delta \rfloor} y_{j,i}^2 \qquad (3)$$

here $h = 1$ is the 30-minute time interval, and T is the total number of 30-minute time intervals in the trading hours for the entire sample period. We assume $\delta \lfloor t/\delta \rfloor = t$ and

$$y_{j,i} = y^*(\delta j + h(i-1)) - y^*(\delta(j-1) + h(i-1)). \qquad (4)$$

The realized bipower variations process is

$$\{y^*_\delta\}_i^{[1,1]} = \{y^*_\delta\}^{[1,1]}(h(i)) - \{y^*_\delta\}^{[1,1]}(h(i-1)), \quad i = 1,2,\ldots,T,$$
$$= \sum_{j=1}^{\lfloor t/\delta \rfloor - 1} |y_{j,i}||y_{j+1,i}|. \qquad (5)$$

The realized quadpower variations process is

$$\{y^*_\delta\}_i^{[1,1,1,1]} = \{y^*_\delta\}^{[1,1,1,1]}(h(i)) - \{y^*_\delta\}^{[1,1,1,1]}(h(i-1)), \quad i = 1,2,\ldots,T,$$
$$= \sum_{j=1}^{\lfloor t/\delta \rfloor - 3} |y_{j,i}||y_{j+1,i}||y_{j+2,i}||y_{j+3,i}|. \qquad (6)$$

Using the above quantities, we can construct the feasible ratio jump test statistic $H_{\delta i}$, which has the asymptotic distribution

$$H_{\delta i} = \frac{\delta^{-1/2}}{\sqrt{\vartheta \{y^*_\delta\}_i^{[1,1,1,1]}/(\{y^*_\delta\}_i^{[1,1]})^2}} \left(\frac{\mu_1^{-2}\{y^*_\delta\}_i^{[1,1]}}{[y^*_\delta]_i} - 1 \right) \to N(0, v), \qquad (7)$$

where the individual test will converge to $N(0, v)$ as $\delta \to 0$, and

$$\mu_1 = E|u| = \sqrt{2}/\Gamma\left(\tfrac{1}{2}\right) = \sqrt{2/\pi} \simeq 0.79788 \qquad (8)$$

and $u \sim N(0,1)$;

$$v = (\pi^2/4) + \pi - 5 \simeq 0.6090. \qquad (9)$$

Given the limitation of the sample interval and the total sample size, we have a limited number of observations to estimate the feasible ratio jump test statistic for the 30-minute interval. To produce better finite sample behavior for small samples, we follow (Barndorff-Nielsen and Shephard 2006) and introduce the feasible adjusted ratio jump test instead of (7):

$$\hat{J}_{\delta i} = \frac{\delta^{-1/2}}{\sqrt{\max[\frac{1}{h}, \{y^*_\delta\}_i^{[1,1,1,1]}/(\{y^*_\delta\}_i^{[1,1]})^2]}} \left(\frac{\mu_1^{-2}\{y^*_\delta\}_i^{[1,1]}}{[y^*_\delta]_i} - 1 \right) \xrightarrow{L} N(0, v),$$

where the individual test will converge to $N(0, v)$ as $\delta \to 0$. Based on this test statistic from Barndorff-Nielsen and Shephard (2006), we would reject the null of a continuous sample path if (10) (J statistic) is significantly negative. In this research, we use Equation (10) to test whether there is jump in the 30-minute interval where i is the index of a certain 30-minute interval and j is the index of a certain 5-minute interval in the corresponding 30-minute interval.

In empirical tests, we take the method of adjusted ratio jump test by checking the value of

$$\left(\frac{\mu_1^{-2}\{y_\delta^*\}_i^{[1,1]}}{[y_\delta^*]_i}-1\right) \tag{11}$$

and *its* corresponding critical value, computed under the assumption of no jump using J statistic. A node which is below the critical value will indicate that there is a jump at that time point (note that J statistic needs to be negative to meet the significance test).

Ifwe identify a jump according to (10), we find that the biggest 5-minute frequency $|Y_{j,i}|$ in the ith 30-minute frequency interval. We identify positive jump if $Y_{j,i} > 0$ and negative jump if $Y_{j,i} < 0$. Then we can get four sequences for positive S&P 500 or crude oil futures price jump, negative S&P 500 or crude oil futures price jump, positive energy ETF jump and negative energy ETF jump, which we mark 1 for jump and 0 otherwise.

3.2. Multivariate Hawkes process

Hawkes process is a class of multivariate point process that models the relationship of event arrivals where the occurrence of an event increases or decreases the probability of the occurrences of future events. Since its introduction in 1971, the Hawkes processand its variantshave beensuccessfully applied to modelseismicevents (Fox, Schoenberg, and Gordon 2016; Molyneux, Gordon, and Schoenberg 2018), community crimes (Mohler, Carter, and Raje 2018; Zhuang and Mateu 2019), social network and social media (Zipkin et al. 2016; Kobayashi and Lambiotte 2016) and biological neuron (Galves and Locherbach 2015; Ditlevsen and Locherbach 2017). Hawkes processes are also becoming more popular in finance literature for its great simplicity and flexibility (Bacry, Mastromatteo, and Muzy 2015). In the last decade, several studies have applied multivariate Hawkes processes on various types of financial market events. Bowsher (2007) develops a new class of generalized Hawkes models and uses it to analyze the interaction mechanism of changes in mid-price quotes and trades arrivals of General Motors shares. Large (2007) applies an appropriate parametric model which views orders and cancelations as a mutually exciting ten-variate Hawkes process to the electronic limit order book of Barclays stock on LSE. Bacry et al. (2013) use a bivariate Hawkes process model to reproduce major high-frequency micro-structural phenomenons, namely the signature plot and Epps effects. Fulop, Li, and Yu (2015) apply a self-exciting process to asset pricing modelin order to captureco-jumps between prices and volatility and self-exciting jump clustering. They identifyself-excitingjump clustering sincethe 1987 market crash and the 2008global financial crisis. More recently, Yanget al. (2018) apply the multivariate Hawkes process to analyze the interaction mechanism between investor sentiment and market return events; Hainaut and Moraux (2019) combine a Hawkes jump-diffusion process with hidden Markov switching model to study economic recession and economic growth.

Market events, such as changes in prices, index valuesor market crashes, can be described as realizations of multivariate point process (PP) $\{T_i, Z_i\}_{i\in\{1,2,\dots\}}$, where T_i is the occurrence time of the ith event, and Z_i indicates the type of the ith event. We denote the M-vector counting process associated with $\{T_i, Z_i\}$ as $N(t) := (N_m(t))_{m=1}^{M}$ with $N_m(t)$ counting the numberof type m events that haveoccurred in $(0,t]$. We denote the natural filtration of the PP $N(t)$ as $\{\mathcal{F}_t^N\}$, which is the information set corresponding to complete observation of $N(t)$ in $[0, t]$. A certain multivariate PP is specified via the vector conditional intensity process $\lambda(t) = (\lambda_m(t))_{m=1}^{M}$ which can be interpreted as the conditionally expected number of type m events per unit time as the time interval tends to zero. We say $\lambda(t)$ is the $(P,\mathcal{F}_t)$-intensity of $N(t)$, where P is the data generating process (DGP) and $\mathcal{F}_t$ is the conditional filtration.

The multivariate Hawkes process is defined by the vector $\{\mathcal{F}_t^N\}$-conditional intensity $(\lambda_1(t), \lambda_2(t), \dots, \lambda_M(t))'$, as

$$\lambda_m(t)=\mu_m(t)+\sum_{j=1}^{k}\tilde{\lambda}_{mm}^{(j)}(t)+\sum_{q=1,q\neq m}^{M}\sum_{j=1}^{k}\tilde{\lambda}_{mq}^{(j)}(t), \tag{12}$$

where $m = 1, 2, \ldots, M$, and $\mu_m(t)$ is a positive deterministic function. In (12), the second term of right-hand side (RHS) generates the self-exciting effect amongevents; the third term ofRHS generates the mutual or cross-exciting effect. Both of these two excitation kernel functions have the form of sums of k exponential kernels.

In this research, we construct two models combining energy ETFs with S&P 500 and crude oil futures price separately. To simplify the problem, we focus on the interaction of the two asset price series: the index and an ETF asset. Foreach asset, we further categorize observations into two types ofevents: positive jump and negative jump. Hence, in each model, we consider four types of event. Following previous similar studies using multivariate Hawkes processes (Large 2007; Bacry et al. 2013; Yang et al. 2018), we choose $j = 1$ and $M = 4$, which represent a 4-dimensional (4-D) Hawkes process (represented by M) with one exponential kernel (represented by j), as

$$\lambda_m(t) = \mu_m + \sum_{n=1}^{4} \sum_{t_j^n < t} \alpha_{nm} e^{-\beta_{nm}(t - t_j^n)}, \tag{13}$$

where μ_m is the rollover effect of the process, assumed to be constant. Furthermore, we impose the constraints that μ_m, α_{nm} and β_{nm} are strictly positive for all m and n. Equation (13) presents a general formof what is known as a mutually exciting Hawkes process. It is important to point out that not all entities share the same intensity. Hence, we propose a parameter estimation process as follows:

(1) Build a 4-D Hawkes process involving S&P 500 with an energy ETF and calibrate all the parameters.
(2) Examine the log-likelihood path to evaluate the quality of estimates.
(3) Change the energy ETF in 4-D Hawkes process and execute step 1-2.
(4) Replace the index ofS&P 500 by crude oil futures price and execute step 1-3.

We estimate the parameters of the multivariate Hawkes process by the maximum likelihood estimation (MLE). The log-likelihood ofa multidimensional Hawkes process can be computed as the sum of the likelihood of each coordinate

$$\ln L(\theta \mid \{t_k^n\}_{n=1,2,\ldots,M}) = \sum_{m=1}^{M} \ln L_m(\theta \mid \{t_k^n\}_{n=1,2,\ldots,M}), \tag{14}$$

where t_k^n is the observed kth time point of event type n, and following Bowsher (2007) we have:

$$\begin{aligned} \ln L_m(\theta \mid \{t_k^n\}_{n=1,2,\ldots,M}) &= -\int_0^T \lambda_m(t \mid \theta)\, dt + \int_0^T \ln \lambda_m(t \mid \theta)\, dN^m(t) \\ &= -\mu_m T - \sum_{n=1}^{M} \sum_{\{k: t_k^n < T\}} \frac{\alpha_{mn}}{\beta_{mn}} \left[1 - e^{-\beta_{mn}(T - t_k^n)}\right] \\ &\quad + \sum_{\{k: t_k^m < T\}} \ln\left[\mu_m + \sum_{n=1}^{M} \alpha_{mn} R_{mn}(k)\right], \end{aligned} \tag{15}$$

with $R_{mn}(k)$ is defined recursively as

$$R_{mn}(k) = e^{-\beta_{mn}(t_k^m - t_{k-1}^m)} R_{mn}(k-1) + \sum_{\{i: t_{k-1}^m \le t_i^n < t_k^m\}} e^{-\beta_{mn}(t_k^m - t_i^n)}. \tag{16}$$

The initial condition $R_{mn}(0) = 0$.

The MLE process for model calibration is at first weset $\alpha = 0$ and $\beta = 10^6$, then optimize μ. We then apply the μ, to the function and fix it, then optimize α and β. The initial value for α and β is 2 and 5, respectively.

3.3. Data collection

In this research, we collect high-frequency data with 5-rninute intervals from Thomson Reuters Tick History (TRTH) database for the top 24 energy ETFs with assets under management (AUM)[4] greater than $100 million (we use this criterion so that we have enough observations to estimate the proposed models). The data range from January 1, 2017 to December 31, 2018, with 730 natural days and 502 trading days. The dataset includes the S&P500 index (SPX) and crude oilfutures contract on NYMEX (CLCl), and 24 energy ETFs (see Appendix Figure Al for a detailed description of these assets).

To gain further insights, we divide the 24 target ETFs into three groups based on their distinct operations: Equity, Master Limited Partnerships (MLPs) and Infrastructure.

(1) Equity: equity shares of energy corporation in oil & gas refining and marketing, and consumable fuels.
(2) Master Limited Partnerships (MLPs): special tax-advantaged entities that derive income from qualified sources such as natural resources.
(3) Infrastructure: equity shares of energy corporations in oil & gas exploration, production, equipment and services.

Figure 1 shows the assets under management (AUM) of the 24 top energy ETF markets in our study. Empirically, the equity and MLP groups share similar distributions in the scale of assets under management.

4. Experiments and discussions

4.1. Jumpdetection

In this section, we take S&P500 (SPX) as an example to show the jump detection process. We divide the daily timeseries into 13 intraday intervals and each interval is 5 minutes in duration. We follow the jump detection methodology in Section 3.1to identify the jumps in which δ isset to 6 and $li = 1$ is fora 30-rninute timeinterval. After scaling, we expect a time series with 6526 intervals (i.e. 13*502) to detect jumps.

Figure 2 shows the Q-Q plot of/ statistic (Equation (10)). It visually shows violation of the normal distribution. But following Barndorff-Nielsen and Shephard (2004), the asymptotic distributional assumption should hold as the sample size increases (in our case, we have 6526 data points), and / statistic can be used to detect jumps. Under the null hypothesis that there are no jumps during the time period, / statistic should follow a normal distribution with a mean equal to zero. The t-test results for J is: $t = 62.783$, $df = 6525$, p-value = 2.2e-16. The alternative hypothesis is the true mean is not equal to zero. The 95 percent confidence

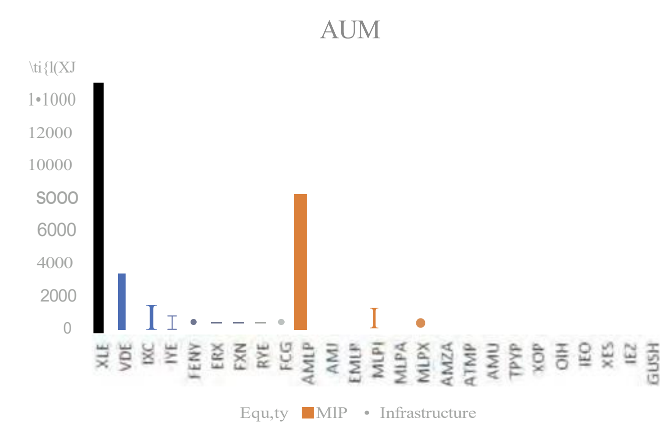


Figure 1. AUM(assets under management - USDin millions).

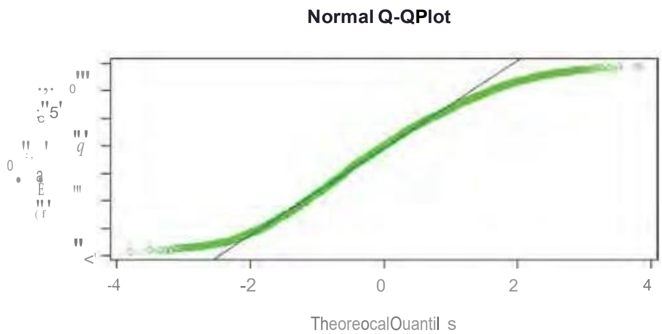


Figure 2. NormalQ-QPlot.

interval is (-0.5802992,-0.5451581).Thesampleestimate mean is -0.5627286. After rejecting the null hypothesis, we still need to determine what is the reasonable number of jumps per day. It dependson the threshold we set, and this threshold is determined based on empirical experience in terms of number of jumps per day in a particular market. Thus, we need to choose a negativevalue as the threshold. If the J statistic is smaller than this threshold, we say there are jumps in this interval corresponding to the J statistic. weset a critical value regarding the J statistic distribution to detect the jumps. For SPX market, we follow the approach used by Yang et al. (2018) to determine the numberof jumps per day for SPX. Hence we set the critical value as -1.66, andit gives around I jump for the trading days.

Figure 3 showsthe distribution of the number of jumps in one day. Most days have Oto1 jump. Figure 4 shows the distribution of jump probability in each interval of a trading day. There are 13 intervals in each trading day, and each one corresponds to a half-hour trading period. For example, I refers to 9:30 to 10:00, 2 refers to 10:00 to 10:30, etc. We find that most of the jumps take place at the beginning of the trading day, which conforms to the theory of information arrival. However, according to volume pattern, there should be an intraday smile graph in the jump distribution, which is not obvious in the SPX example. But we did find this phenomenon in some other ETFs jump graph like AMLPs.

We repeat the jump detection process for all energy ETFs. During each process, we record the critical value weuse as threshold, the average total jumps per day,as well as the average number of positive jumps to compute the positive jump ratio.

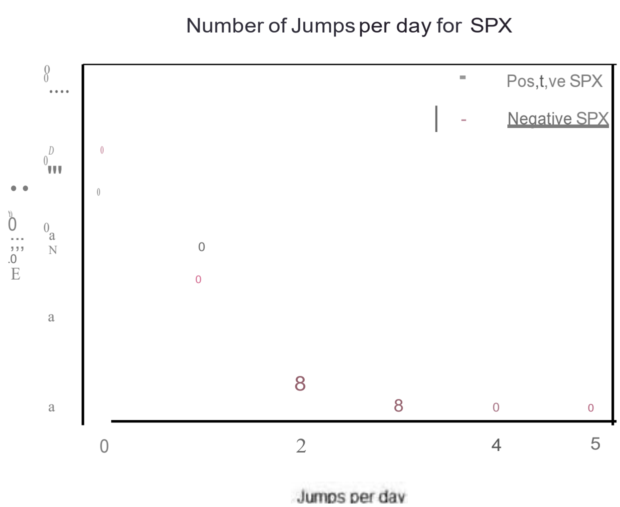


Figure 3. Jump times perday.

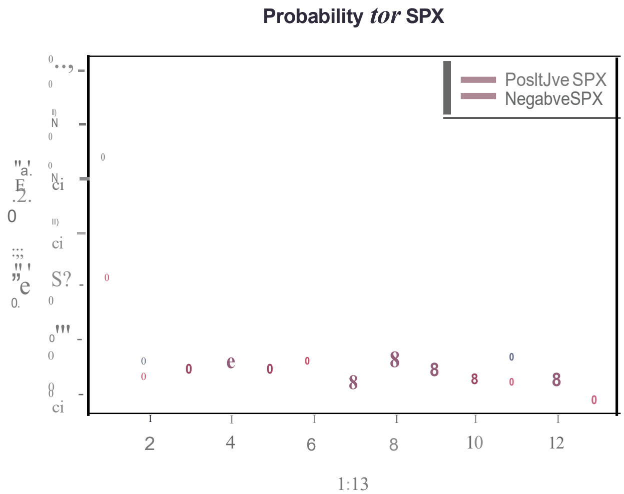


Figure 4. Jump probability per interval.

Figure S. Critical valuefor *J* statistic.

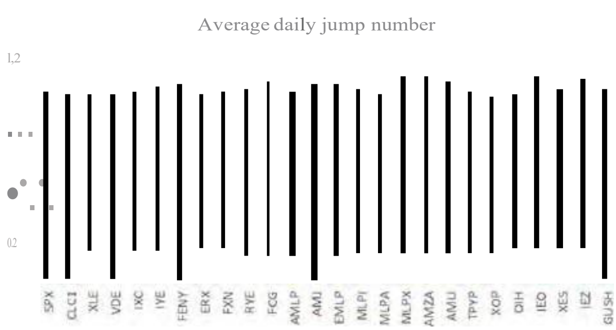
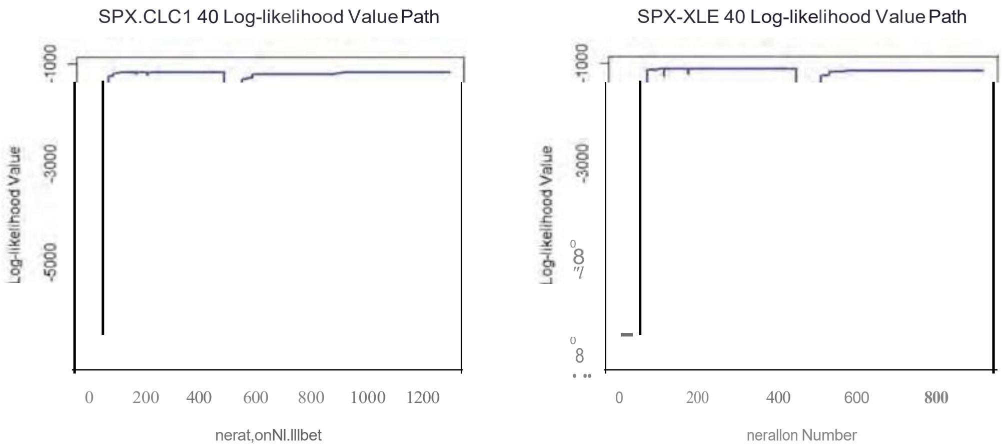


Figure 6. Average daily jump number.

Figure 5 shows the distribution of critical values we use as threshold for each asset. As we expect a similar average daily jump number, so the critical values are varying from asset to asset. Figure 6 shows the distribution of average daily jump numbers foreach asset. We can see that most assets have **1** jump per day. We also calculate the jump ratios for each ETF. The results show that most assets have a percentage around 0.5, which means that the positive jumps versus negative ones are almost half to half.



(a) SPX-CLCl 40 Log-likelihood Value Path. (b) SPX-XLE -ID Log-likelihood Value Path.

Figure 7. 4DLog-likelihood Convergence.Thex-axis represents the iteration number, and the y-axis representsthe log-likelihood value. (a)SPX-CLCl 4DLog-likelihood Value Path.(b) SPX-XLE 4DLog-likelihood Value Path.

4.2. Modelestimation

In thissection, wediscuss the convergence ofour model estimates using maximum likelihood estimation (MLE). In general, we find the 4-D multivariate Hawkes processes exhibit consistency in their convergence property. Here, wetakeSPX-CLCl and SPX-XLE examples of 4-D Hawkes process model to show the qualityof maximum likelihood estimation process.

Figure 7 shows the log-likelihood value path of the two examples to check the quality of our estimation. 4-D SPX-CLCl model converges to a value smaller than 0.000001 after 1200 iterations and 4-D SPX-XLE model converges to a value smaller than 0.00000l after 800 iterations. We also check the convergence of the estimated parameters. Overall, we can say that the model has a good convergence performance in the estimation process as it was approved byBacry et al. (2013).

4.3. Indexmodel parameter results

In thissection, weanalyze the jump contagion between SPX and CLCl.Table 1 shows the statistics of the parameters for the 4-D Hawkes model ofSPX and CLCl jump events. Through the analysis, we can draw the following conclusions: (1) The arrival rateof positive index jumps ($\mu_{,1}$ and $\mu_{,3}$) is greater than that of negative index jumps ($\mu_{,2}$ and $\mu_{,4}$). (2) From SPX perspective, only α_{21} and α_{41} are relatively large, while other α_{nm} values are very small. This means that both negative SPXand negative CLCl jump events lead to positive SPX jumps. (3) From CLCl perspective, α_{23}, α_{24}, α_{43} and α_{44} are relatively large, while other α_{ij} values are very small. This means the negativeSPX jump events leadto both CLCl positive and negative jump events; negativeCLCI jump eventslead to both CLCl positive and negative jump events. (4) For both of the two indices, the values of β_1 and β_2 rows are smaller than the valuesof β_3 and β_4 rows. Overall, we find negative index jumps lead index pricediscovery processes, and their influences disappear faster than the positive index jumps.

4.4. Rollover effect

In Hawkes process, μ represents rollover effect. It denotes the basic intensity, which depends onlyon the event itself. This value represents the expected jump times in each interval of the time series. $\mu_{,1}$ and $\mu_{,2}$ represent the basic attributes of indices, and we focus on μ_3 and μ_4 to find the attributes of the target energy ETF. As $\mu_{,3}$ and $\mu_{,4}$ represent the basic attributes of a specific ETF, as a result, it should be the same regardless of the indices in the model.

Ta.hie 1. Parameterestimated for models between SPX and CLCl.

	1 (Positive)	2 (Negative)	3 (Positive)	4 (Negative)
μ,	0.0449	0.0337	0.0431	0.0342
IX1.	1.676e-5	1.952e-5	4.19e-6	4.23e-5
IXz.	0.010923	0.104128	0.0408	4.53e-5
IX3.	4.601e-5	1.230e-5	8.78e-6	8.71e-6
IX4.	0.052463	0.117473	0.0111	6.90e-5
/Ji.	4.749442	4.717247	4.7245	4.7207
lh	4.%5026	4.982888	5.0102	4.9772
th	4.775073	4.801%5	4.7923	4.8090
/J4.	5.018251	5.009097	4.9984	4.%93

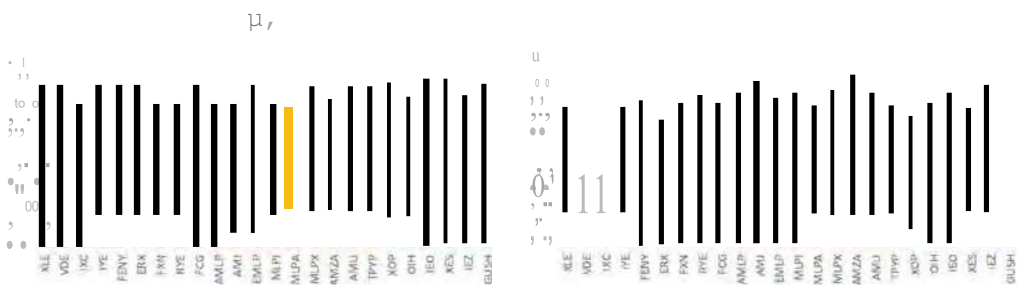


Figure 8. μ,3 and μ,4 for each energy ETF.

Table 2. Statistics of μ,3 and $\mu,4$ for each group.

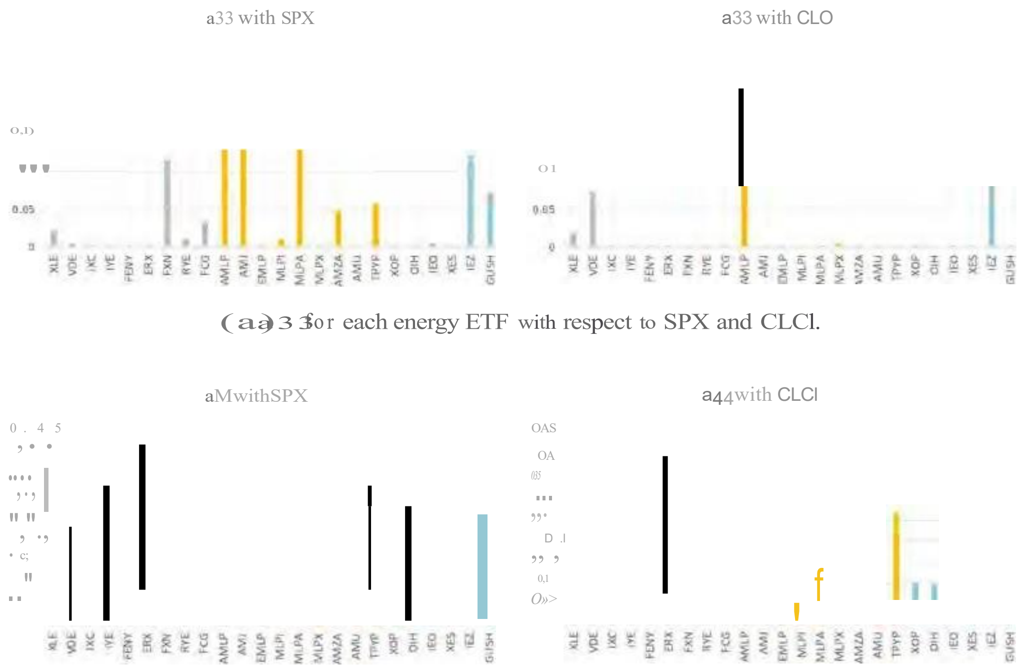
	Equity		MLP		Infrastructure	
	Mean	Median	Mean	Median	Mean	Median
μ,3	0.0413	0.0409	**0.0399**	**0.0401**	0.0422	0.0429
$\mu,4$	0.0372	0.0380	**0.0403**	**0.0405**	0.0377	0.0370

Figure 8 and Table 2 show the results of μ,3 and $\mu,4$. Obviously, ETFs from MLP grouphas a smaller valueof $\mu,3$ than the other two groups, which means that these ETFs have less expected positive jumps. ETFs from MLP group hasagreatervalueof $\mu,4$ than the other twogroups, which means that these ETFs have moreexpected negative jumps. The relative high rollover effect can be interpreted as high persistence or stronger auto-correlation than the other energy ETF groups.

4.5. *Exciting effect*

In Hawkes process, a represents the exciting effect. Self-exciting effect, which is represented by a33 and a_{44}, is the effect within the same type jumps of ETFs. The a33 is the self-exciting effect of the positive jumps, and the a_{44} is the self-exciting effect of the negative jumps. Theoretically, the a33 and a_{44} are different with respect to SPX and CLCl for the reason that the positive and negative jumps of the index influence the likelihood estimation of all the parameters. When the positive and negative jumps of the index change from SPX to CLC1, the relationship between all the four types ofjump events are entirely changed. The estimation will re-compute all the parameters from a different path, instead of keeping the parameters of au and a_{22}, just changing other parameters.

Figure 9 and Table 3 show the results of a33 and a_{44}, which is the self-exciting effect of positive jumps and negative jumps of ETF. We find that all the a33 and a_{44} are positive, which means the happening of a jump will increase the occur probability of the next jump of the same type. For the ETFs from Equity group and Infrastructure group, to both SPX and CLCl, a_{44} is obviously larger than a33, which means negative jumps will have a greater influence on next negative jump compared with positive ones on next positive jump. We



(a) α_{33} for each energy ETF with respect to SPX and CLCl.

(b) α_{44} for each energy ETF with respect to SPX and CLCJ.

Figure 9. α_{33} and α_{44} for SPX and CLCl. (a) α_{33} for each energy ETF with respect to SPX and CLCl. (b) α_{44} for each energy ETF with respect to SPX and CLCl.

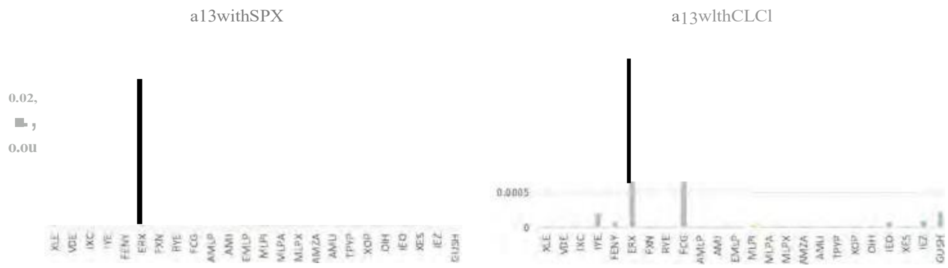
Table 3. Statistics of α_{33}, α_{44} for each group.

		Equity		MLP		Infrastructure	
		Mean	Median	Mean	Median	Mean	Median
α_{33}	SPX	0.0211	0.0048	**0.0740**	**0.0482**	0.0333	0.0031
	CLCl	0.0103	5.83e-5	**0.0235**	**0.0001**	0.0164	1.58e-5
α_{44}	SPX	0.1696	0.1105	**0.0621**	**0.0006**	0.1338	0.1282
	CLCl	0.0816	0.0159	**0.0526**	**0.0001**	0.0635	0.0762

also see that MLP group has the greater α_{33} compared with the Equity group and Infrastructure group, which indicates that MLP group has the largest self-exciting jumps for positive returns. The MLP group has the least α_{44} compared with the Equity group and Infrastructure group, which indicates that MLP group has least self-exciting jumps for negative returns. In other words, this group of ETFs is relatively stable to negative return jumps.

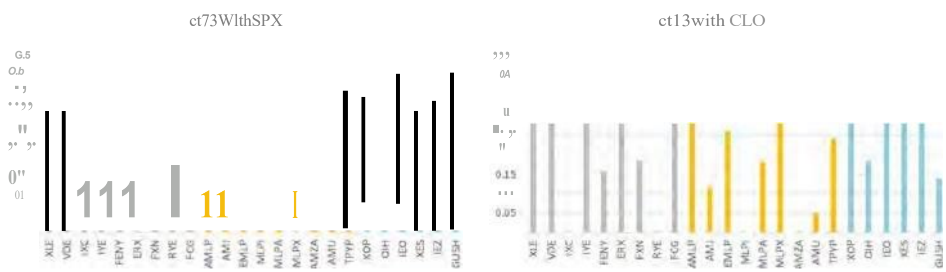
Cross-exciting effect is the effect from event n to event m. It means how the probability of the event n's occurrence will increase the probability of event m. Now, we focus on α_{13}, α_{14}, α_{23} and α_{24} to show how the market indices would lead ETF jump events.

Figure 10 shows the results of α_{13}, α_{14}, α_{23} and α_{24} of the 4-D Hawkes process models. In each figure, the left one is the model with SPX as the index and the right one is the model with CLCl as the index. Table 4 shows the statistics of α_{13}, α_{14}, α_{23} and α_{24} for each group. Through the analysis, we can draw the following conclusions: (1) All of the α_{nm} are positive, which means that the jump of indices will 'lead' the jump of target ETF, no matter whether the jumps are positive or negative. (2) Both α_{13} and α_{14} of the three ETF groups are very small, which means that positive jumps of the index have very little influence on the ETF jumps. (3) For α_{23}, to the SPX index, the value of the Infrastructure group is the largest; while the value of the Equity group is the smallest. For α_{23}, to the CLCl index, the value of the Infrastructure group is the largest; while the value of the MLP group is the

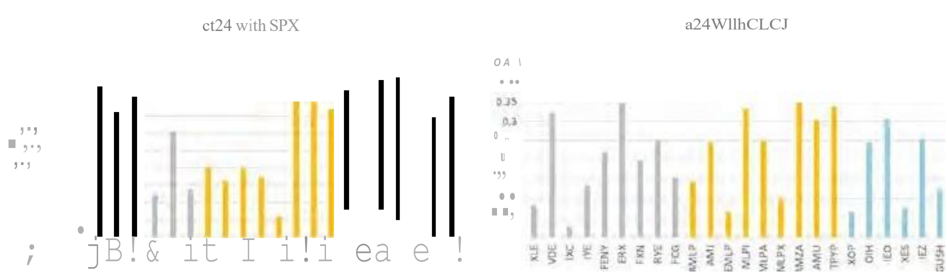


(a) a:13 for b<1seline SPX and CLCl.

(b) o:14 for baseline SPX a.nd CLCL



(c) a:23 for baseline SPX and CLCl.



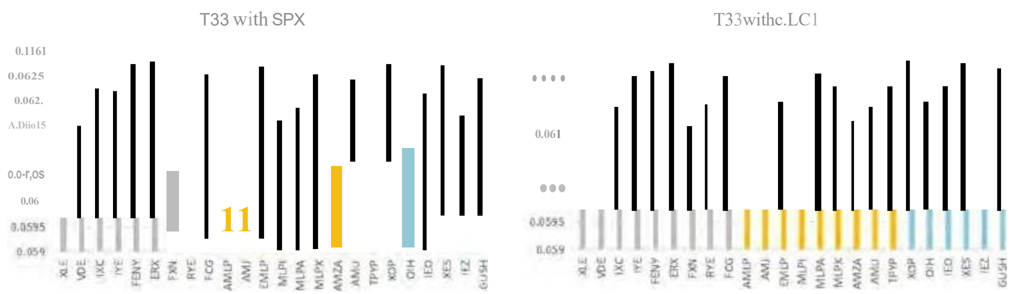
{d) a:24 for baseline SPX and CLCl.

Figure 10. *cxlj* between SPX/CLCl and ETFs. (a) a:13 for baseline SPX and CLCl. (b) cx14 for baseline SPX and CLCl. (c) *cx13* for baseline SPX and CLCl. (d)cx24 for baseline SPX and CLCl.

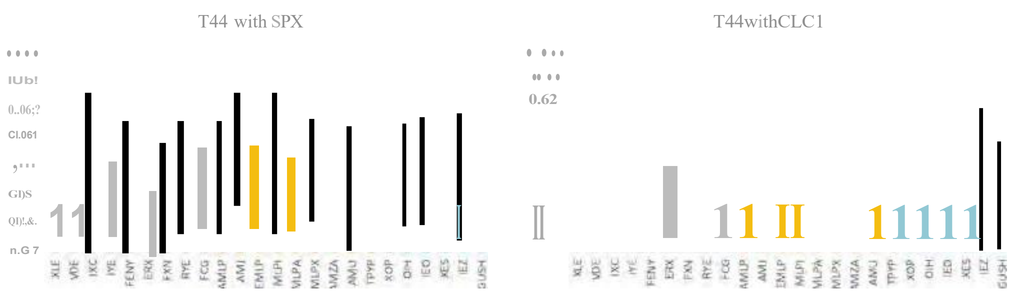
smallest. (4) For a_{24}, to the SPX index, the valueof the MLP group is the smallest. For a_{24}, to the CLCl index, the valueof the MLP group is the largest. Overall, the influence of the negative jumps from both SPX and CLCl is much stronger than the influence of the positive index jumps.

Table 4. Statistics of013,014, 023and024 foreach group.

		Equity		MLP		Infrastructure	
		Mean	Median	Mean	Median	Mean	Median
013	SPX	0.0032	6.98e-6	8.26e-5	1.14e-5	1.55e-5	1.33e-5
	CLCl	0.0004	2.62e-5	1.59e-5	1.Ble-5	7.09e-5	4.28e-5
014	SPX	1.03e-5	9.60e-6	2.54e-5	1.69e-5	8.20e-6	6.62e-6
	CLCl	7.53e-5	1.91e-5	0.0073	8.32e-6	0.0003	1.18e-5
023	SPX	0.2438	0.2565	0.2529	0.2871	0.3659	0.3708
	CLCl	0.2295	0.3105	0.1759	0.1809	0.2700	0.3100
024	SPX	0.2903	0.3507	0.2668	0.2016	0.2817	0.3637
	CLCl	0.1930	0.1985	0.2441	0.2491	0.1784	0.1844



(a) $T33$ for each energy ETF with respect to SPX and CLCl.



(b) $T44$ for each energy ETF with respect to SPX and CLCl.

Figure 11. T33and $T44$for SPXand CLCl.(a) T33 for each energy ETFwith respect to SPX and CLCl. (b) $T44$ for each energy ITT with respectto SPX and CLCl.

Table 5. Statistics of T33, $T44$ for each group.

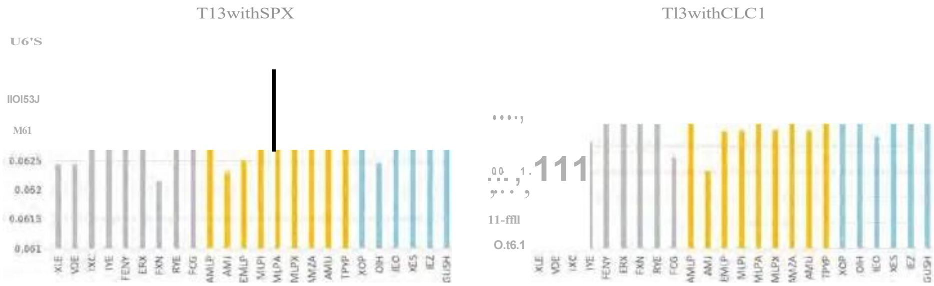
		Equity		MLP		Infrastructure	
		Mean	Median	Mean	Median	Mean	Median
Tn	SPX	0.0620	0.0622	0.0617	0.0619	0.0621	0.0623
	CLCl	0.0618	0.0618	0.0613	0.0614	0.0619	0.0620
$T44$	SPX	0.0611	0.0611	0.0616	0.0615	0.0608	0.0610
	CLCl	0.0605	0.0606	0.0613	0.0612	0.0604	0.0605

4.6. Time-decaying effect

In Hawkes process models, $f3$ represents the time decaying effect. $f3mn$measures the decaying speed of the effect from event n to event m. In this research, we introduce the half-life metric to measure the decaying effect and show the jump decaying speed. It is defined as:

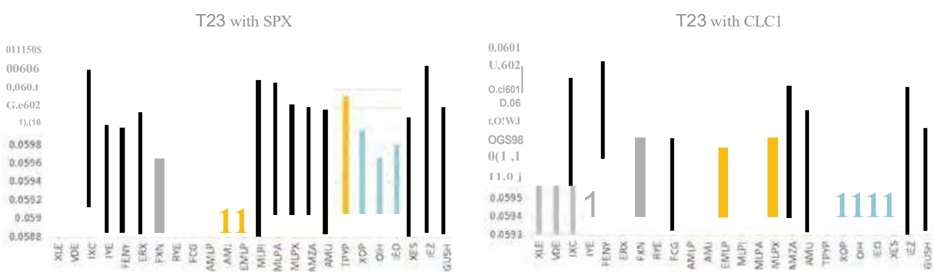
$$T_{\frac{1}{2}}=-\frac{log2}{\beta}, \tag{17}$$

where the smaller the T, the greater the decaying effect.

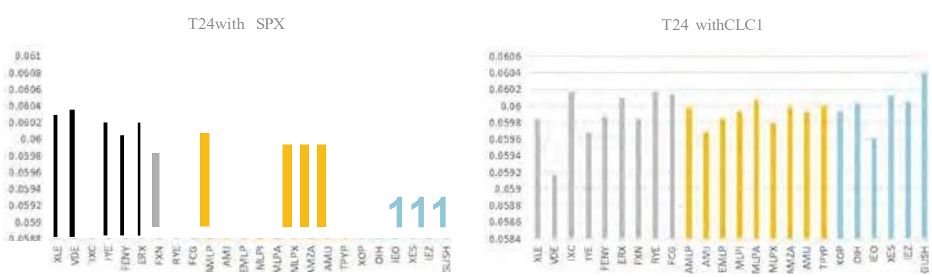


(a) T_{13} for SPX and CLCL

(b) T_{14} for SPX and CLCL



(c) T_{23} for SPX and CLCl.



(d) T_{24} for SPX and CLCl.

Figure 12. T_q for SPX and CLCl.(a) T_{13} for SPX and CLCl.(b) T_{14} for SPX and CLCl.(c) T_{13} for SPX and CLCl. (d) T_{24} for SPX and CLCl.

Table 6. StatisticsofTn, T14, Tn and T24 for eachgroup.

		Equity		MLP		Infrastructure	
		Mean	Median	Mean	Median	Mean	Median
Tn	SPX	0.0630	0.0632	0.0633	0.0634	0.0632	0.0633
	CLCl	0.0620	0.0621	0.0620	0.0619	0.0621	0.0621
T14	SPX	0.0638	0.0638	0.0635	0.0636	0.0634	0.0635
	CLCl	0.0620	0.0621	0.0622	0.0622	0.0621	0.0622
Tn	SPX	0.0600	0.0599	0.0601	0.0602	0.0600	0.0600
	CLCl	0.0599	0.0600	0.0600	0.0600	0.0599	0.0599
fi4	SPX	0.0601	0.0602	0.0602	0.0601	0.0602	0.0602
	CLCl	0.0599	0.0599	0.0599	0.0599	0.0600	0.0600

Figure 11 shows the distribution ofT for /h3 and {3*44*, which is the time-decaying effectwithin the sametypes of jump events or self-excitation (positive jumps of ETF to positive jumps ofETF and negative jumps ofETF to negative jumps of ETF). These parameters indicate the inner attribute of ETFs. Table 5 shows the statistics of T_{33} and T_{44} for each group. From the results, we can draw the following conclusions: (1) The decaying effects of both positive jumps and negative jumps are similar among all ETFs, which all are around 0.061.This is about 1.83 minutes. (2) For the T_{44}, the valueof the MLP group is a little larger than the other two groups.

Figure 12 shows the results of *Tu,* T_{14}, T_{23}, T_{24} for the 4-D Hawkes process model. The left figure is the model with SPX as the indices and the right figure is the model with CLCl as the indices. Table 6 shows the statistics of *Tu,* T_{23}, T_{14} and T_{24} for each group. Through the analysis, we can draw the following conclusions: (1) There is hardly any difference in T_{13}, T_{14}, T_{23} and T_{24} values of models, for they share a very similar scale around 0.06.This is about 1.8 minutes. (2) For all ETFs in the three groups, the T of SPX model is larger than T in the CLCl model. This means that the decaying effect of SPX is slower than CLCI,showing that equity market has a longer influence on them, but the differences are not very large.

4.7. Accumulated contagion effect

As a robustness check, we define $F_{ij}(h)$ to measure the expected jump effect of event i to event j in the future h interval. In our case, we set $h = 1$, which is 30 minutes. For example, if Fu(I) for SPX equals 0.1, then it means a positive jump ofSPX will cause 0.1 positive ETF jump in the next 30 minutes. The F metric is defined as:

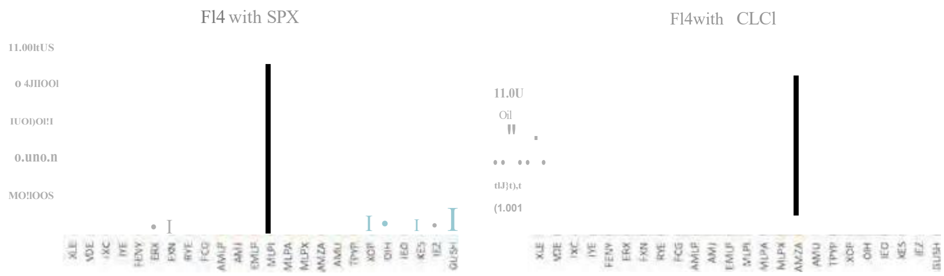
$$F_{ij}(h) = \frac{a_{ij}^{*}\,(ef3_{ij}h - 1)}{/3i^{*}j} \qquad (18)$$

Figure 13 shows the results of *Fu,* F_{14}, F_{23} and F_{24} for the 4-D Hawkes process model. The left figure is the model with SPX as the index and the right figure is the model with CLCl as the index. Through the analysis, we can draw the following conclusions: (1) The distribution of Fis very similar to that of *as* that we discussed earlier. This result shows that the jump of indices would positively excite the jumps of ETF assets, no matter the jump is positive or negative. (2) Both the *Fu* and F_{14} of the three groups are very small. (3) For F_{23}, to the SPX index, the value of the Infrastructure group is the largest; while the valueof the Equity group is the smallest. For F_{23}, to the CLCl index, the value of the MLP group is the smallest. (4) For F_{24}, to the SPX index, the value of the MLP group is the smallest. For F_{24}, to the CLCl index, the valueof the MLP group is the largest.

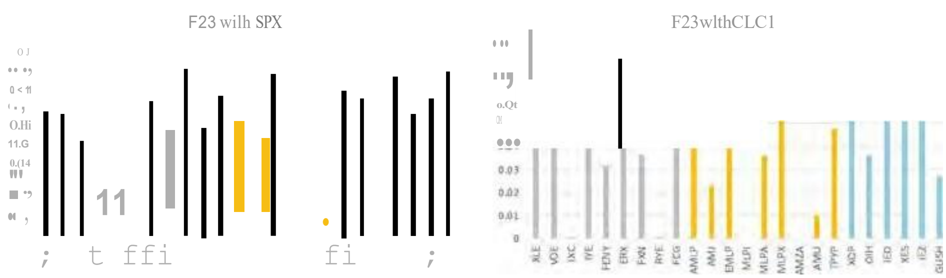
5. Conclusion

In thisstudy, we model jump events in S&PSOO, crude oil futures price and 24 energy ETF markets using multivariate Hawkes Processes. The multivariate Hawkes Process helps us deciphering the occurrence of an event on the occurrence of future events of the same or different types, and yet it does not require stationarity condition on dataobservations. We consequently construct two multivariate Hawkes process models based on the

(a.) F13 for SPX and CLCl.



(b) F_{14} for SPX and CLCL



(c) F_{23} for SPX and CLCl.

(d) F2.t for SPX and CLCl.

Figure 13. F_{q} for SPX and CLCl. (a) F_{13} for SPX and CLCl. (b) F14 for SPX and CLCl. (c) F_{23} for SPX and CLCl. (d) F_{24} for SPX and CLCl.

baseline S&P500 index and crude oil futures price separately. To gain further insight, we divide the target energy ETFs into three groups, i.e. equity group, MLP group, and infrastructure group. Analyzing the estimated model parameters, we are able to interpret the complex relationship of various jump events regarding their rollover, excitation, time-decaying effect and accumulated contagion effects.

First, we examine the jump rollover effect or persistence of jumps. We find that the ETFs from MLP group havea smaller value of μ_3 than the other two groups, which means that these ETFs have less expected positive jumps. ETFs from MLP group have a greater value ofμ_4 than the other two groups, which means that these ETFs have more expected negative jumps. For self-exciting effect, all the *as* are positive, which means there exists consistent self-exciting effect within all ETF markets. For the ETFs from Equity group and Infrastructure group, to both SPX and CLCI, a_{44} is obviously larger than a_{33}, which means negative jumps will have a greater influence on the next negative jump compared with positive ones on next positive jump. We also see that MLP group has the greater a_{33} compared with the Equity group and Infrastructure group, which indicates that MLP group has largest self-exciting jumps for positive returns. The MLP group has the least a_{44} compared with the Equitygroup and Infrastructuregroup,which indicates that MLPgroup hasleast self-exciting jumps for negative returns. For cross-exciting effect, both a_{13} anda_{14} of the three ETF groups are very small, which means that positive jumps of the index have very little influence on the ETF jumps. For a_{23}, to the SPX index, the valueof the Infrastructure group is the largest; while the value of the Equity group is the smallest. For a_{23}, to the CLCI index, the value of the Infrastructuregroup is the largest; while the valueof the MLP group issmallest. For a_{24}, totheSPX index, the value of the MLP group is the smallest. For a_{24}, to the CLCI index, the value of the MLP group is the largest. For the self contagion time decaying effect, the decaying effects between positive jumps and negative jumps are similar among all ETFs, which all are around 0.061. For the T_{44}, thevalue of the MLP group is a little larger than the other two groups. For mutual-time-decaying effect, there is hardly any difference in T_{13}, T_{14}, T_{23} and T_{24} values of models, for they share a very same scale around 0.06. For all ETFs in the three groups, the T of SPX model is larger than T in the CLCI model. This means that the decaying effect of SPX is slower than CLCI, showing that equity market has a longer influence on ETFs, but the differences are not very big. For the accumulated effect factor, the conclusion is consistent with the observation from the a!nmS. For the jump contagion between indices, μ_3 is greater than μ_4 for both SPX and CLCI. In SPX-CLCI model, the a_{23} and a_{43} are relatively large, while other aij values are very small. This means the negative jump of SPX leads to the positive jump of CLCI; the negative jump of CLCI leads to the positive jump of CLCI. In CLCI-SPX model, a_{23}, a_{24}, a_{43} anda_{44} are relatively large, while other aij values are very small. This means the negative jump events lead to the other jump events. The values of /Ji and fh rows are smaller than the values of fh and {34 rows. Overall, the index pricediscovery process seems to start with negative jumps, while the influence from the negative jumps disappear faster than the positive jumps.

In general, our findings are consistent with the existing literature that the energy ETFs share some common attributes with other ETFs that return jumps are highly correlated with equity market as well as the crude oil futures. However, our findings reveal a much richer understanding than the previous studies using high-frequency market data with multivariate Hawkes processes. We are able to show jump contagion effect or the flow of the market jump events. We find that both S&PS00 index and crude oil futures negative jumps lead the ETF price discovery process. When we look deeper into the different groups of the ETFs, we find that on average, the self contagion in negative jumps is stronger than theself contagion in the positive jumps across all ETF groups. However, the ETFs focused on the master limited partnership (MLP) segment showless negative jump contagion and are least influenced by the jumps of the market indies than the other energy ETFs. Overall, the influence of negative jumps on ETFs from both the equity index and the energy future index is stronger than that of the positive jumps. And the influence of the equity index (S&PS00) jump on ETFs lasts longer than that of energy future index (CLC1). It sheds light on the advantage of thiskind of partnership organization in energy investment.

Notes

1. Energy Equity ETFs invest primarily in stocks of naturalgas,oil,and alternative energy companies which include major energy companies such as Exxon-Mobile Corp. (XOM) and Duke Energy Corp. (DUK), as well as smaller, fast-growing companies in the energy sector.
2. An MLP is a publicly traded partnership (PTP); this is the term used in the U.S. tax code. It is a partnership, or a limited liability company {LLC) that haschosen partnership taxation, that trades on a public excl1ange such as NYSE, NASDAQ etc., or over-the-counter (OTC) market A significant number of MLPs do not operate businesses but are simply investment fw1ds.

3. Energy Infrastructure ETFs invest in portfolios of companies that derivea substantial portion of their revenues from operating or providing services in support of infrastructureassets such as pipelines, power transmission and petroleum and natural gas storage in the petroleum, natural gas and power generation industries.
4. The data are fromhttp://ETF.com on December I, 2018.

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Appendix

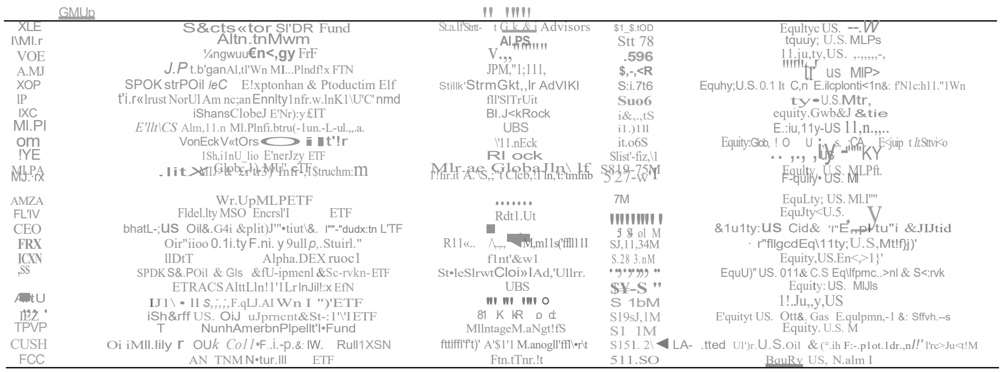

Figure A1. Energy ETFs assets list.

Table A1. Statistics of each energy ETFs.

Ticker	Group	AUM	Average volume	3-year standard deviation	3-year total return
XLE		15100	12,997,846	19.02	5.28%
VOE		3590	329,696	20.24	4.20%
IXC		1510	424,330	16.56	7.83%
IYE		858.62	581,188	19.49	3.86%
FENY		480.85	218,620	19.96	3.84%
ERX		341.34	3,208,704	56.9	-0.14%
FXN		283.22	206,420	25.19	-1.76%
RYE		205.16	62,272	24.29	3.55%
FCG	1	112.86	258,045	26.46	-4.26%
AMLP	2	8570	16,696,098	17.56	4.88%
AMJ	2	2950	2,052,316	18.42	4.95%
EMLP	2	2200	579,403	11.58	8.45%
MLPI	2	1370	632,453	18.12	4.90%
MLPA	2	819.75	901,180	18.64	4.57%
MLPX	2	527.49	603,754	18.94	10.14%
AMZA	2	496.87	752,514	24.06	6.61%
ATMP	2	408.14	89,443	17.81	10.28%
AMU	2	246.85	102,811	17.96	5.05%
TPYP	2	178.02	55,904	15.24	11.90%
XOP	3	2710	19,697,538	29.33	16.15%
OIH	3	1080	6,974,125	32.31	22.81%
IEO	3	384.01	83,406	24.05	5.08%
XES	3	277.02	1,313,856	37.67	-11.66%
IEZ	3	195.61	126,162	32.57	-9.17%
GUSH	3	151.52	6,462,837	87.77	-24.28%