Energy 140 (2017) 837–849

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Return volatility duration analysis of NYMEX energy futures and spot

Hongli Niu [a, *], Jun Wang [b]

[a] Donlinks School of Economics and Management, University of Science and Technology Beijing, Beijing 100083, China
[b] School of Science, Beijing Jiaotong University, Beijing, 100044, China

ARTICLE INFO

Article history:
Received 16 September 2016
Received in revised form
8 September 2017
Accepted 11 September 2017
Available online 14 September 2017

Keywords:
Energy market
Futures and spot
Volatility duration
Probability distribution
Complexity behaviors
Multiscale analysis

ABSTRACT

Return volatility plays a key role in quantifying risk, optimizing the portfolio and pricing modelling of financial market. The study focusing on the return volatility of energy market can help greatly understand the energy fluctuating behaviors. In this paper, we introduce a concept of volatility duration into the analysis of the New York Mercantile Exchange (NYMEX) energy market, where the daily closing prices of the futures and spot for the crude oil, natural gas, heating oil and propane are adopted. The volatility duration is defined as the shortest passage time that the future's volatility intensity takes to go beyond or below the current volatility intensity which is time-varying and considered as the basic intensity reference. Then, two main aspects of the statistical properties analysis for the energy volatility duration time series are focused on: one is about the empirical probability distributions and their scaling behaviors are observed; another is about the complexity properties of the energy volatility durations, which are discussed by the entropy measures of the composite multiscale entropy (CMSE) and the composite multiscale cross-sample entropy (CMSCE) approaches.

1. Introduction

Oil has played a prominent role in shaping the economic and political developments of modern economies and our everyday life. Understanding oil return volatility is of significant interest to both investors and policymakers [1–5], because return volatility contributes to the risk quantification, the portfolio optimization [6–8], and key input provision of option pricing models that are based on the estimation of the volatility of the asset [7,9]. Under varying market conditions, investors in the financial industry are always faced with the challenge of how to choose a portfolio and make it more optimal, since large and unpredictable fluctuations are usually constitute risk for investments. Apart from caring the future's volatility intensity above or below a predefined large value (usually referred to extreme volatility), investors usually tend to make decision by taking *today's* risk (or volatility) as a basic reference and wonder how long it will take the *future's* risk to go above or below the *current volatility* intensity, to some extent like an investment horizon. If it is locally falling (compared with the "tomorrow" volatility), one is interested in the minimum time that it takes for the future's volatility intensity to exceed the current value, vice verse. Taking these into consideration, Niu et al. [10] proposed a concept of daily return volatility duration for financial stock indexes, which is defined as the shortest passage time when the future volatility intensity is above or below the current volatility intensity. The probability distribution, memory effects and multifractility properties of the volatility duration series were meanwhile explored. In the present paper, we continue the former work and introduce the volatility duration concept into the study of the energy futures and spot for the crude oil, the natural gas, the heating oil and the propane from the New York Mercantile Exchange (NYMEX).

The idea of the volatility duration is somewhat inspired by the study of the waiting time between two successive events, which has recently drawn much attention from various perspectives. The research is performed for example on the intertrade duration between two consecutive trades [11–13], the duration time that the price or volatility keeps below or above its initial value [14], the waiting time that the price return first exceeds a predefined level [15,16], and the mean exit time which is the mean time when the random process leaves for the first time a given interval [17], etc… In particular, many literature have studied the return intervals or recurrence intervals τ between successive "extreme" volatilities whose values are greater than a threshold q [18–24]. For instance, Yamasaki et al. [23] investigated the return intervals between volatility above a certain threshold in the US stock and foreign

* Corresponding author.
E-mail address: niuhongli@ustb.edu.cn (H. Niu).

http://dx.doi.org/10.1016/j.energy.2017.09.046
0360-5442/

exchange markets, and found that the distribution function $P_q(\tau)$ scales with the mean return interval $\overline{\tau}$ as $P_q(\tau) = \overline{\tau}^{-1} f(\tau/\overline{\tau})$, and $f(x)$ is consistent with a power-law form. They also found the strong memory effects of the return intervals. Wang et al. [21] studied the return intervals in intraday data of the US market, and found similar scaling and the scaling function $f(x)$ can well approximated by a stretched exponential $f(x) \sim e^{ax^{\gamma}}$. Zhang et al. [24] used an alternative function $f(x) \sim e^{a(\ln x)^{\gamma}}$ to fit the distribution. Bogachev and Bunde [18] showed that the probability density functions of the interoccurrence times (between events above some threshold) for multifractal data sets from the multiplicative random cascades and the multifractal random walks models are governed by power laws with exponents that depend explicitly on the considered threshold. Different in the way of predefining threshold q in the return interval analysis, the threshold in the process of volatility duration is time-varying, which refers to the current volatility intensity. The detailed definition can be found in Section 2.

Then we investigate the statistical properties of the volatility duration series for the energy futures and spot. Over the last few decades, international financial markets have experienced a comprehensive fluctuation behaviors study of the financial price variations such as the fat tails phenomenon, power law of logarithmic returns and volumes, volatility clustering, multifractality of volatility, complexity, etc. [24–33]. In this work, we firstly perform a study of the empirical probability distribution and the cumulative distribution of the volatility durations, which is fundamental but crucial in understanding a statistical variable. Interestingly, the scaling behaviors of the distributions for the analyzed energy futures and spot are observed. The typical behavior for scaling is data collapse, all curves can be “collapsed” onto a single curve after a certain scale transformation on the measure [34]. A system obeys a scaling law if its relation is characterized by the same functional form and exponent over a certain range of scales (“scale invariance”). We secondly exploit the underlying complexity properties of the volatility duration time series. Entropy is an useful complexity measure for dynamic system. A family of entropy measures, such as Shannon entropy [35], Kolmogorov entropy [36], approximate entropy (ApEn) [37], sample entropy (SampEn) [38], ect., have witnessed wide applications in various fields. Taking the multiple time scales into SampEn estimation, Costa et al. [39,40] proposed the multiscale entropy (MSE) for complex time series analysis, which has demonstrated the effectiveness when applied to analysis of various types of data in the past decades. The application fields include the human gait dynamics [40], heart rate variability [39], vibration of rotary machine [24], financial markets [32,41], etc.. However, Wu et al. [42] pointed out the estimation reliability remains questionable when the MSE method is applied for short-term time series, and proposed a modification algorithm called composite MSE, which has been verified its effectiveness in analysis of short-term financial time series [32]. In this paper, we adopted it to explore the complexity properties of the energy volatility durations. On the other hand, cross-sample entropy [38] is an extension of MSE and provides an indication of the degree of synchronizing between two concurrent time series. Based on MSE and cross-sample entropy, Yan et al. [43] developed a novel algorithm, termed multiscale cross entropy (MSCE), to assess the coupling behaviors between two sequences on multiple scales. In this paper, we introduce and apply the composite multiscale cross-sample entropy (CMSCE) method [44], which is a combination of CMSE and MSCE methods, to measure asynchrony behaviors between the energy futures' volatility durations and the energy spot's volatility durations.

On the whole, the main contribution of this work includes the following aspects: firstly a concept called volatility duration which was proposed in study of financial stock market is introduced into the return volatility study of energy markets. Secondly the empirical probability density function and tail distribution of volatility durations for the energy products are studied. It will show that their empirical probability distribution can be depicted by a power law function, and their tail distribution can be described by stretched exponential function. Lastly, the complexity properties of energy markets are investigated of returns and volatility durations by a entropy measure, namely CMSE method, and the relationship between each energy item's futures and spot, as well as among different energy products are analyzed by the CMSCE approach from the complexity asynchrony perspective.

The paper is organized as follow. In Section 2, there is the definition of the return volatility duration. In Section 3, the adopted data sets of NYMEX energy futures and spot are illustrated, including the crude oil, the natural gas, the heating oil and the propane. Section 4 investigates the probability distribution and cumulative distribution of the energy volatility durations. In Section 5, the empirical results of complexity and synchrony of the volatility durations are demonstrated, meanwhile the applied CMSE and CMSCE approaches are introduced. In Section 6, the paper is closed with conclusions.

2. Concept description of volatility duration

We here for the first time introduce a concept of volatility duration into the analysis of energy markets. Denote $P(t)$ the daily price of a energy item at time t. Its normalized volatility time series is given as follows

$$v(t) = \frac{V(t)}{\left[\left\langle V^2(t)\right\rangle - \left\langle V(t)\right\rangle^2\right]^{1/2}}, \tag{1}$$

where $V(t) = |\log P(t) - \log P(t-1)|$ is the volatility series represented by the absolute logarithmic returns of the prices. Then a volatility duration series $\{D(t), t = 1, 2, \ldots, T\}$ is produced from $v(t)$ in the following way: At each day t, we consider the normalized volatility on the next day $v(t+1)$. If $v(t+1) < v(t)$, we say that the volatility is locally falling at t, and define the volatility duration length $I(t)$ at time t as the waiting time τ when $v(t+\tau)$ at the first time exceeds $v(t)$, namely,

$$I(t) = \max\{\tau : \quad v(t+i) < v(t), \quad \text{for} \quad i \le \tau\} \tag{2}$$

Here $I(t)$ represents the first and also the shortest passage time when the future volatility of stock prices overtakes the current volatility, see the case of $I(t) = 12$ in Fig. 1 for a graphical illustration. If $v(t+1) > v(t)$, we say that the volatility is locally rising at t, and similarly define the volatility duration length $I(t)$ at time t as the waiting time τ when $v(t+\tau)$ is below $v(t)$ at the first time, that is,

$$I(t) = \max\{\tau : \quad v(t+i) > v(t), \quad \text{for} \quad i \le \tau\} \tag{3}$$

The case of $I(t) = 5$ in Fig. 1 is one example. For rare case $v(t+1) = v(t)$, we have $I(t) = 0$. Then the final volatility duration is taken as the square root of $I(t)$, in order to weaken the extreme values in volatility duration series,

$$D(t) = \begin{cases} +\sqrt{I(t)}, & \text{If} \quad v(t+1) > v(t) \\ -\sqrt{I(t)}, & \text{If} \quad v(t+1) < v(t) \end{cases}, \tag{4}$$

where the positive and negative sign at each data point $I(t)$ is used to represent and also distinguish the case when the future volatility is relatively rising or falling with respect to the current one.