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Detrended fluctuation analysis on spot and futures markets of West Texas Intermediate crude oil

Yudong Wang [a,*], Yu Wei [b], Chongfeng Wu [a]

[a] Antai College of Economics & Management, Shanghai Jiao Tong University, Fahuazhen Road 535, Shanghai, PR China

[b] School of Economics & Management, Southwest Jiaotong University, The First Section of Northern Second Ring Road, Chengdu, Sichuan Province, PR China

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ABSTRACT

In this paper, we study the auto-correlations and cross-correlations of West Texas Intermediate (WTI) crude oil spot and futures return series employing detrended fluctuation analysis (DFA) and detrended cross-correlation analysis (DCCA). Scaling analysis shows that, for time scales smaller than a month, the auto-correlations and cross-correlations are persistent. For time scales larger than a month but smaller than a year, the correlations are anti-persistent, while, for time scales larger than a year, the series are neither auto-correlated nor cross-correlated, indicating the efficient operation of the crude oil markets. Moreover, for small time scales, the degree of short-term cross-correlations is higher than that of auto-correlations. Using the multifractal extension of DFA and DCCA, we find that, for small time scales, the correlations are strongly multifractal, while, for large time scales, the correlations are nearly monofractal. Analyzing the multifractality of shuffled and surrogated series, we find that both long-range correlations and fat-tail distributions make important contributions to the multifractality. Our results have important implications for market efficiency and asset pricing models.

1. Introduction

The detrended fluctuation analysis (DFA) proposed by Peng et al. [1] has been widely used to detect the long-range correlations in financial time series [2–10]. This method can be used to investigate the long-range correlations embedded in the non-stationary series, and it overcomes the drawback of conventional rescale range analysis [11]. DFA can also avoid the spurious detection of apparent long-range correlations that are an artifact of patchiness. It has been proven that the DFA method can outperform R/S analysis even over short size time series [12] and short times [13]. There are two important extensions of DFA. One is the multifractal form (MF-DFA) proposed by Kantelhardt et al. [14], which is also widely employed to investigate multifractality in financial markets [15–20]. The other extension is the detrended cross-correlation analysis (DCCA) proposed by Podobnik and Stanley [21]. The DCCA method can be used to detect the cross-correlations between two non-stationary financial time series [22]. Similarly to the extension to MF-DFA, Zhou [23] extends DCCA to its multifractal form which can be used to detect the multifractality of cross-correlations.

Crude oil is one of the major commodities in the world, and it is the basis of industrialization. Crude oil plays an important role in all economies. Thus, the oil price has become an increasingly important topic for governments, enterprises and investors. The oil price is easily affected by many market internal and external factors, such as speculation, economic recession and geopolitical events. These factors make the oil price fluctuate frequently. For instance, the West Texas Intermediate (WTI) crude oil price was higher than 145 US dollars per barrel in July 2008. However, as a result of the financial crisis, the oil

* Corresponding author.
E-mail address: wangyudongnj@126.com (Y. Wang).

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price decreased by about 80%, and was only about 33 US dollars per barrel at the end of 2008. In an attempt to understand the complexity of crude oil markets, the market microstructure has been widely studied in a few papers [24–30]. Specifically, using the DFA method, Alvarez-Ramirez et al. [26] found that the long-term behavior of crude oil markets was efficient and that the short-term positively correlated behavior was progressively weaker over time. Wang and Liu [27] found that the correlated behaviors which are overall progressively weaker over time are different for different time scale intervals, using multiscale analysis. Based on MF-DFA, the evidence in [28,29] suggests that the crude oil markets are multifractal and that the main sources of multifractality are long-range correlations. Alvarez-Ramirez et al. [30], using a lagged DFA, also found evidence of inefficiency in a crude oil market.

However, the existing works mainly focus on the correlations of crude oil spot markets; very few papers concentrate on the auto-correlations of another important market, the futures market. Moreover, the previous work on the auto-correlated behavior in crude oil markets was mainly based on DFA or MF-DFA. There has been no work on the cross-correlated behavior between spot and futures markets. Based on these considerations, our contributions in this paper are as follows. (1) Employing DFA and DCCA, we investigate the auto-correlated behavior in, and cross-correlated behavior between, crude oil spot and futures markets. Evidence from multiscale analysis shows that, for monthly and yearly time scales, the cross-correlations between two individual series are generally stronger than what would be expected from the auto-correlated behavior of each of the individual series. (2) Using the multifractal forms of DFA and DCCA, we find that the multifractality of auto-correlations and cross-correlations are the strongest for time scales smaller than a month. Moreover, the multifractality of the cross-correlations is stronger than those of the auto-correlations of each individual series for time scales smaller than a month. Both long-range correlations and fat-tail distributions make important contributions to the multifractality. For time scales larger than a year, the multifractality of the auto-correlated and cross-correlated behaviors was significantly weaker, indicating more efficient operations in the long term. Some implications of our results on the dynamics of crude oil markets are also discussed.

This paper is organized as follows. The next section provides the methodology. Section 3 introduces sample data some statistical characteristics. Section 4 shows the empirical results. Section 5 provides some relevant discussions. The last section presents the conclusion.

2. Methodology

Multifractal detrended cross-correlation analysis (MF-DCCA) [23] can be described as follows.

Step 1. Consider two time series, $\{x_t, t = 1, \ldots, N\}$ and $\{y_t, t = 1, \ldots, N\}$, where N is the equal length of these two series. Then, we describe the "profile" of each series, and get two new series, $xx_k = \sum_{t=1}^{k}(x_t - \bar{x})$ and $yy_k = \sum_{t=1}^{k}(y_t - \bar{y})$, $k = 1, \ldots, N$.

Step 2. Divide both profiles $\{xx_k\}$ and $\{yy_k\}$ into $N_s = \mathrm{int}(N/s)$ non-overlapping segments of equal length s. Since the length N of the series is often not a multiple of the considered time scale s, a short part at the end of each profile may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end of each profile. Thereby, $2N_s$ segments are obtained together. We set $10 < s < N/5$.

Step 3. Calculate the local trends $\widetilde{xx}_{(\lambda-1)s+j}$ and $\widetilde{yy}_{(\lambda-1)s+j}$ for each of the $2N_s$ segments by a least-squares fit of each series. Then determine the co-moved variances

$$F^2(s, \lambda) \equiv \frac{1}{s}\sum_{j=1}^{s}[xx_{(\lambda-1)s+j} - \widetilde{xx}_{(\lambda-1)s+j}][yy_{(\lambda-1)s+j} - \widetilde{yy}_{(\lambda-1)s+j}] \tag{1}$$

for $\lambda = 1, 2, \ldots, N_s$ and

$$F^2(s, \lambda) \equiv \frac{1}{s}\sum_{j=1}^{s}[xx_{N-(\lambda-N_s)s+j} - \widetilde{xx}_{N-(\lambda-N_s)s+j}][yy_{N-(\lambda-N_s)s+j} - \widetilde{yy}_{N-(\lambda-N_s)s+j}] \tag{2}$$

for $\lambda = N_s + 1, N_s + 2, \ldots, 2N_s$. The trends $\widetilde{xx}_{(\lambda-1)s+j}$ and $\widetilde{yy}_{(\lambda-1)s+j}$ can be computed from linear, quadratic or high-order polynomial fits of each profile for segment λ.

Step 4. Average over all segments to get the fluctuation functions

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{\lambda=1}^{2N_s}[F^2(s, \lambda)]^{q/2}\right\}^{1/q} \tag{3}$$

for any real value $q \neq 0$ and

$$F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{\lambda=1}^{2N_s}\ln[F^2(s, \lambda)]\right\}. \tag{4}$$

Step 5. Analyze the scale behavior of the fluctuation function through observing the log–log plots of $F_q(s)$ versus s. If two series are long-range cross-correlated, we can obtain a power-law relationship as follows

$$F_q(s) \sim s^{h(q)}. \tag{5}$$