A study of correlations between crude oil spot and futures markets: A rolling sample test

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ABSTRACT

In this article, we investigate the asymmetries of exceedance correlations and cross-correlations between West Texas Intermediate (WTI) spot and futures markets. First, employing the test statistic proposed by Hong et al. [Asymmetries in stock returns: statistical tests and economic evaluation, Review of Financial Studies 20 (2007) 1547–1581], we find that the exceedance correlations were overall symmetric. However, the results from rolling windows show that some occasional events could induce the significant asymmetries of the exceedance correlations. Second, employing the test statistic proposed by Podobnik et al. [Quantifying cross-correlations using local and global detrending approaches, European Physics Journal B 71 (2009) 243–250], we find that the cross-correlations were significant even for large lagged orders. Using the detrended cross-correlation analysis proposed by Podobnik and Stanley [Detrended cross-correlation analysis: a new method for analyzing two nonstationary time series, Physics Review Letters 100 (2008) 084102], we find that the cross-correlations were weakly persistent and were stronger between spot and futures contract with larger maturity. Our results from rolling sample test also show the apparent effects of the exogenous events. Additionally, we have some relevant discussions on the obtained evidence.

1. Introduction

The futures markets have two important functions. The first one is to hedge and reduce the potential risk for investors and practitioners. The other is the mechanism of price discovery. These two functions are based on the theory that the futures prices can reflect the expectation of investors which is one of the important determinants of price mechanism. Theoretically, the futures prices are equal to the spot prices in the future. However, it is almost always not consistent with the reality because of the transaction cost and market noise. Thus, it is worth having an examination of correlations between spot and futures markets. Especially, for crude oil markets, the relationship between spot and futures market has been investigated extensively. For example, Quan [1], Schwarz and Szakmary [2], and Gulen [3] detected the correlations between oil spot and futures markets using the methods of cointegration proposed by Engle and Granger [4] and Johansen [5]. However, the above cointegration methods do not consider the shock on the correlations caused by the structural break and do not imply that the cointegrating vectors have the property of time invariance. Similar studies can also be found in Serletis and Banack [6], Cologni and Manera [7], and Chen and Lin [8]. As argued in Bekiros and Diks [9], the recent empirical evidence on the relationship between spot and futures markets is invariably based on the Granger test [10]. Although it requires the linearity assumption, this approach is appealing. In fact, the nonlinear structure has been a “stylized fact” in financial

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markets. For this consideration, Bekiros and Diks [9] investigated the linear and nonlinear causal linkages between daily spot and futures prices for maturities of one, two, three and four months of WTI crude oil. Besides the conventional Granger test, Bekiros and Diks [9] detected the nonlinear causal relationship not only between raw data series using a nonparametric test for nonlinear causality, but also between VECM and GARCH-BEKK residual series. Their results showed that WTI crude oil spot and futures markets displayed asymmetric GARCH effects and/or statistically significant higher order conditional moments. Huang et al. [11] investigated the dynamics of a nonlinear relationship between crude oil spot and futures prices and found that the nonlinear model was clearly superior to that of the linear model. Different from previous works, in this paper, we investigate the relationships between crude oil spot and futures markets in the perspective of cross-correlation and exceedance correlation.

As the presence of auto-correlations in crude oil markets which has been extensively investigated in the existing literature [12–18] implies the predictability and market inefficiency, the cross-correlations also have some implications and have been studied in some of the previous works [19–32]. First, it implies that the predictability of spot (futures) prices can be improved based on the analysis of the history data of futures (spot) prices. Second, it also implies the market inefficiency because under the efficient market hypothesis, the dynamics of prices are dominated by randomness and cannot be predicted technically.

Motivated by the fact that many physical and financial systems display power-law correlations together with an asymmetry in the probability distribution [33], we investigate the exceedance correlations between crude oil spot and futures returns, asymmetry property between upside moves and downside moves in financial markets [34–36]. Obviously, the presence of asymmetric correlations can cause problems in hedging effectiveness. Then, if all of the other assets tend to fall together as one kind of asset falls, the traditional investment theory which suggests the diversification in optimal portfolio allocation is also questionable.

As far as we know, there are very few investigations on the exceedance correlations or cross-correlations between crude oil spot and futures prices. The only exception is the work of Wang et al. [37]. Their results indicates that the spot and futures prices and volatilities are long-range cross-correlated. However, Wang et al. [37] study cross-correlations between crude oil spot price series and 1 month futures price series only, not between spot price and futures prices with other maturities. Moreover, Wang et al. [37] only analyze the cross-correlations between two whole series. Their overall analysis cannot show the evolutions of correlations over time. Third, Wang et al. [37] do not analyze the asymmetry property of correlations between upside moves and downside moves.

Comparing to the work in Wang et al. [37], our contributions are as follows: (1) We investigate the exceedance correlations between WTI crude oil spot and four futures price series and test for the asymmetries using the method proposed by Hong et al. [36]. (2) Qualitatively, we investigate the cross-correlations using the statistic introduced by Podobnik et al. [21]. Quantitatively, we also study the cross-correlations using the detrended cross-correlation analysis proposed by Podobnik and Stanley [19]. (3) Employing the rolling sample test, we study the evolution of local asymmetric correlations and cross-correlations, and find the apparent influence of some exogenous events on the two kinds of correlations. Some economic implications of our results are also discussed.

This paper is organized as follows: the next section provides the methodology description. We show the data description and preliminary analysis in Section 3. We get the empirical results in Section 4 and some relevant discussions in Section 5. Then, we conclude the article in the last section.

2. Methodology

2.1. Asymmetries of exceedance correlations

Following Longin and Solnik [34], Ang and Chen [35] and Hong et al. [36], we consider the exceedance between two series. The correlation at exceedance level c is defined as the correlation between two variables when both of them exceed c standard deviations away from their means, respectively,

\[ \rho^+(c) = \text{corr}(R_{1t}, R_{2t}|R_{1t} > c, R_{2t} > c), \]

\[ \rho^-(c) = \text{corr}(R_{1t}, R_{2t}|R_{1t} < -c, R_{2t} < -c), \]

where, following Ang and Chen [35] and Hong et al. [36], the returns are always standardized to be zero mean and unity variance. The null hypothesis of symmetric correlations is

\[ H_0 : \rho^+(c) = \rho^-(c), \text{ for all } c \geq 0. \]

If the null hypothesis is rejected, there must be the asymmetric correlations. The alternative hypothesis is

\[ H_1 : \rho^+(c) \neq \rho^-(c), \text{ for some } c \geq 0. \]

\[ ^1 \text{In Ref. [33], a stochastic process was proposed that can model both properties.} \]
For the pair of time series, \( \{R_{1t}, R_{2t}\} \), the length is \( T \). Let \( T^+_c \) be the number of observations in which both \( R_{1t} \) and \( R_{2t} \) are larger than \( c \) simultaneously. We can get the conditional means and variances

\[
\hat{\mu}^+_1(c) = \frac{1}{T^+_c} \sum_{t=1}^{T} R_{1t} \cdot I(R_{1t} > c, R_{2t} > c),
\]

(5)

\[
\hat{\mu}^+_2(c) = \frac{1}{T^+_c} \sum_{t=1}^{T} R_{2t} \cdot I(R_{1t} > c, R_{2t} > c),
\]

(6)

\[
\hat{\sigma}^2_1(c)^2 = \frac{1}{T^+_c - 1} \sum_{t=1}^{T} [R_{1t} - \hat{\mu}^+_1(c)]^2 \cdot I(R_{1t} > c, R_{2t} > c),
\]

(7)

\[
\hat{\sigma}^2_2(c)^2 = \frac{1}{T^+_c - 1} \sum_{t=1}^{T} [R_{2t} - \hat{\mu}^+_2(c)]^2 \cdot I(R_{1t} > c, R_{2t} > c),
\]

(8)

where \( I(\cdot) \) is the indicator function. We can get the exceedance correlation

\[
\hat{\rho}^+(c) = \frac{1}{T^+_c - 1} \sum_{t=1}^{T} \hat{X}^+_1(c) \hat{X}^+_2(c) \cdot I(R_{1t} > c, R_{2t} > c),
\]

(9)

where

\[
\hat{X}^+_1(c) = \frac{R_{1t} - \hat{\mu}^+_1(c)}{\hat{\sigma}^+_1(c)}, \quad \hat{X}^+_2(c) = \frac{R_{2t} - \hat{\mu}^+_2(c)}{\hat{\sigma}^+_2(c)}.
\]

Similarly, we can define the expression for \( \hat{\rho}^+(c) \).

After having defined the specific form of the exceedance correlations, we employing the method in Hong et al. [36] test the asymmetries of the correlations. The advantage of the test is model-free and not dependent on the hypothesis of the return distribution. The test statistic can be described as,

\[
J_\rho = T(\hat{\rho}^+ - \hat{\rho}^-)' \hat{\Omega}^{-1}(\hat{\rho}^+ - \hat{\rho}^-),
\]

(10)

where,

\[
\hat{\Omega} = \sum_{t=1}^{T-1} k(\ell/p) \hat{y}_i.
\]

(11)

\( \hat{\Omega} \) is an \( N \times N \) matrix with \( (i, j) \)th element

\[
\hat{y}_i(c_i, c_j) = \frac{1}{T} \sum_{t=|i|+1}^{T} \hat{\xi}_t(c_i) \hat{\xi}_t-|i|(c_j),
\]

(12)

and

\[
\hat{\xi}_t(c) = \frac{T}{T^+_c} [\hat{X}^+_1(c) \hat{X}^+_2(c) - \hat{\rho}^+(c)] \cdot I(R_{1t} > c, R_{2t} > c) - \frac{T}{T^+_c} [\hat{X}^+_1(c) \hat{X}^+_2(c) - \hat{\rho}^-(c)] \cdot I(R_{1t} < -c, R_{2t} < -c); \]

(13)

and \( k(\cdot) \) is a kernel function that assign a suitable weight to each lag of order \( l \), and \( p \) is the smoothing parameter or lag truncation order. Following the suggestion in Hong et al. [36], we use the Bartlett kernel,

\[
k(z) = (1 - |z|) \cdot I(|z| < 1)
\]

(14)

which is popular and is used by Newey and West [38] and others.

However, we have to obtain the value of \( p \) to compute the statistic. As an alternative choice in Hong et al. [36], we determine the value of \( p \) by the Newey and West [38] procedure.

Let \( J_\rho \), be the same \( J_\rho \), statistic except using \( \hat{\rho} \), the data driven \( p \). Hong et al. [36] prove that the statistics \( \hat{J}_\rho \) and \( J_\rho \) obey the \( \chi^2 \) distribution with \( m \) degrees of freedom. Where, \( m \) is the number of different threshold values \( c \).

2.2. Testing for the cross-correlations

We investigate the nonlinear cross-correlations between history spot (futures) and future futures (spot) returns. Podobnik et al. [21] introduced a cross-correlation statistic in analogy to the Ljung–Box (LJB) test [39]. For two time series,
\[ x_t, \ t = 1, \ldots, N \] and \( \{y_t, \ t = 1, \ldots, N\} \), the test statistic

\[ Q_{cc}(m) = N^2 \sum_{i=1}^{m} \frac{X_i^2}{N-i}. \tag{15} \]

Here, the cross-correlation function

\[ X_i = \frac{\sum_{k=i+1}^{N} x_k y_{k-i}}{\sqrt{\sum_{k=i+1}^{N} x_k^2 \sum_{k=i+1}^{N} y_k^2}}. \tag{16} \]

The cross-correlation statistic \( Q_{cc}(m) \) is approximately \( \chi^2(m) \) distributed with \( m \) degrees of freedom. The statistic can be used to test the null hypothesis that none of the first \( m \) cross-correlation coefficient is different from zero. This statistic was proposed for both small and large samples, and generally should be employed for returns, not original time series. Clearly, when applied for original time series, the test gives qualitative estimate about the presence of cross-correlations in time series.

However, the cross-correlation test based on the statistics in Eq. (15) can only be used to test the presence of cross-correlations qualitatively. In order to test the presence of cross-correlations quantitatively, we need the detrended cross-correlation analysis proposed by Podobnik and Stanley [19]. Podobnik and Stanley [19] proposed DCCA and used it to study the cross-correlations of both of returns and volatilities between Nasdaq and Dow Jones. Podobnik et al. [22] also reported cross-correlations between the (abs) trading volume changes and the (abs) price changes for the SP500 index employing DCCA. DCCA, which can be used to investigate the cross-correlations between two nonstationary time series, is described as follows,

First, we can get the profile as two new series,

\[ X_k = \sum_{i=1}^{k} (x_i - \bar{x}) \quad \text{and} \quad Y_k = \sum_{i=1}^{k} (y_i - \bar{y}), \quad k = 1, \ldots, N. \tag{17} \]

Second, divide the both profiles \( \{X_k\} \) and \( \{Y_k\} \) into \( N_s = \text{int}(N/s) \) nonoverlapping 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 \( 10 < s < N/5 \). Then, we calculate the local trends \( \tilde{X}_{(\lambda-1)s+j} \) and \( \tilde{Y}_{(\lambda-1)s+j} \) for each of the \( 2N_s \) segments by a least-squares fit of each series. Then determine the co-moved variance

\[ F^2(s, \lambda) \equiv \frac{1}{s} \sum_{j=1}^{s} [X_{(\lambda-1)s+j} - \tilde{X}_{(\lambda-1)s+j}] [Y_{(\lambda-1)s+j} - \tilde{Y}_{(\lambda-1)s+j}] \tag{18} \]

for \( \lambda = 1, 2, \ldots, N_s \) and

\[ F^2(s, \lambda) \equiv \frac{1}{s} \sum_{j=1}^{s} [X_{N-(\lambda-N_s)s+j} - \tilde{X}_{N-(\lambda-N_s)s+j}] [Y_{N-(\lambda-N_s)s+j} - \tilde{Y}_{N-(\lambda-N_s)s+j}] \tag{19} \]

for \( \lambda = N_s + 1, N_s + 2, \ldots, 2N_s \). The trends \( \tilde{X}_{(\lambda-1)s+j} \) and \( \tilde{Y}_{(\lambda-1)s+j} \) can be computed from linear, quadratic or high order polynomial fit of each profile for segment \( \lambda \). After that, we need to average over all segments to get the fluctuation function

\[ F(s) = \sqrt{\frac{1}{2N_s} \sum_{\lambda=1}^{2N_s} F^2(s, \lambda)}. \tag{20} \]

At last, we should analyze the scaling behavior of the fluctuation function by observing the log-log plots of \( F(s) \) versus \( s \). If two series are long-range cross-correlated, as a power-law

\[ F(s) \sim s^{\alpha}. \tag{21} \]

The exponent \( \alpha \) can be obtained by observing the slope of log-log plot of \( F(s) \) versus \( s \) by ordinary least squares (OLS). If scaling exponent \( \alpha > 0.5 \), the cross-correlations between two series are persistent. An increase of spot (futures) price is likely to be followed by an increase of the futures (spot) price. If scaling exponent \( \alpha < 0.5 \), the cross-correlations between two series are anti-persistent. An increase of spot (futures) price is likely to be followed by a decrease of the futures (spot) price. In this case, just like the mean-reversion behavior related to the auto-correlations, we can define that the oil prices display the property of cross-mean-reversion. After a certain period, the spot (futures) prices will be likely to go back to the history futures (spot) prices. If \( \alpha = 0.5 \), there are no apparent long-range cross-correlations.
### Table 1
Descriptive statistics of returns of WTI spot and futures prices.

<table>
<thead>
<tr>
<th>WTI spot</th>
<th>WTI F1</th>
<th>WTI F2</th>
<th>WTI F3</th>
<th>WTI F4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (%)</td>
<td>0.025</td>
<td>0.025</td>
<td>0.025</td>
<td>0.026</td>
</tr>
<tr>
<td>Maximum (%)</td>
<td>18.87</td>
<td>16.41</td>
<td>13.79</td>
<td>12.12</td>
</tr>
<tr>
<td>Minimum (%)</td>
<td>−40.64</td>
<td>−40.05</td>
<td>−38.41</td>
<td>−32.82</td>
</tr>
<tr>
<td>Std. deviation (%)</td>
<td>2.62</td>
<td>2.54</td>
<td>2.23</td>
<td>2.06</td>
</tr>
<tr>
<td>Skewness</td>
<td>−0.88</td>
<td>−0.91</td>
<td>−1.17</td>
<td>−1.01</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>16.25</td>
<td>16.62</td>
<td>20.49</td>
<td>15.57</td>
</tr>
</tbody>
</table>

Note: This table provides the descriptive statistics of WTI spot and futures prices. ADF, PP and KPSS denote the t-statistics of Augment Dickey–Fuller, Phillips–Perron and Kwiatkowski–Phillips–Schmidt–Shin unit root tests, respectively. Denotes the rejection of the null hypothesis at 1% significant level.

### Table 2
The estimation of tail exponents.

<table>
<thead>
<tr>
<th>Spot</th>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hill estimator</td>
<td>2.985</td>
<td>3.115</td>
<td>3.336</td>
<td>3.368</td>
</tr>
<tr>
<td>Podobnik's beta</td>
<td>2.754</td>
<td>2.834</td>
<td>3.335</td>
<td>3.461</td>
</tr>
</tbody>
</table>

### 3. Data and preliminary analysis

We choose daily spot and futures prices of West Texas Intermediate (WTI) crude oil with the date from Jan 2, 1990 to Dec 31, 2009, covering the period about 20 years in total. The futures price series contain four price series of futures contract traded in New York Mercantile Exchange (NYMEX) with maturities of one, two, three and four months.

Let $P_t$ be the price of a crude oil on day $t$. The daily price return, $r_t$, is calculated as its logarithmic difference, $r_t = \log(P_t) - \log(P_{t-1})$. We provide the descriptive statistics of five return series in Table 1. The sample means of five return series are very near to zero, quite small in comparison to the standard deviations. The standard deviation of spot return series is the largest among five series and those of futures series decrease with the maturity increases. The Jarque–Bera statistics show that the null hypothesis of normality is rejected at the 1% level of significance, also as evidenced by high excess kurtosis and negative skewness. The Ljung–Box statistics for serial auto-correlations show that the null hypothesis of no auto-correlations up to the 20th order is rejected at 1% significant level and confirms the existence of auto-correlations in the five return series. The augment Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests both support the rejection of the null hypothesis of a unit root at the 1% significance level indicating that the five return series are stationary. The Kwiatkowski–Phillips–Schmidt–Shin unit root statistics which cannot reject the stationarity null also support the result of stationary time series.

We show the figure illustrations of five standardized return series in Fig. 1. For the convenience of description, we use F1, F2, F3 and F4 to denote futures returns with maturities of 1, 2, 3 and 4 months.

To further investigate the fat-tail distributions, we employ a new method of power-law estimation proposed by Podobnik et al. \[29\] which can be described as follows. On average, there is one volatility above threshold $q$ after each time interval $\bar{\tau}_q$, then

$$1/\bar{\tau}_q \approx \int_q^\infty P(|x|)d|x| = P(|x| > q) \sim q^{-\beta}. \quad (22)$$

Then, we calculate the average time interval $\bar{\tau}_q$ for different values of $q$, and obtain estimates of $\beta$ through the relationship,

$$\bar{\tau}_q \propto q^\beta. \quad (23)$$

Fig. 2 provides the log–log plots of average time interval $\bar{\tau}_q$ versus threshold $q$.\[2\] We choose the values of $q$ varying from 1 to 6 with a fixed step of 0.5. We can find the apparent power-law relationships. Table 2 reports the estimates of Podobnik's tail exponents $\beta$ for both spot and futures return series. The $\beta$ for futures return series are slightly larger than those for spot return series, indicating that the distributions of futures returns are more fat tailed. The reason may be that futures markets contain more noise than spot market, such as speculations.

\[2\] To save space, we only show the situation for WTI spot returns and futures returns with maturity of 1 month.
Fig. 1. Returns of WTI spot and futures prices.

To confirm the results obtained from Podobnik’s $\beta$ values, we use an alternative method of Hill [40]. The Hill exponent $\beta$ is estimated by sorting the normalized returns by their size, $x_1 > x_2 > \cdots > x_N$, with the result [40],

$$\beta = (N - 1) \left[ \sum_{i=1}^{N-1} \ln \frac{x_i}{x_N} \right]^{-1},$$

where, $N - 1$ is the number of data points in the tail part. We take the criterion that $N$ does not exceed 5% of the sample size. Table 2 also reports the results of tail exponents of Hill. We can find that Hill exponents are close to 3, which are strongly consistent to results obtained from Podobnik’s $\beta$.

4. Empirical results

4.1. The asymmetries of exceedance correlations

Table 3 provides the exceedance correlations between returns of WTI spot and four futures contract and also provides the $p$-values of the asymmetry test. We choose seven exceedance levels $c$, 0, 0.5, 1, 1.5, 2, 2.5 and 3. We can find that for a constant level $c$, the correlation coefficient under the condition of negative returns $\hat{\rho}^-(c)$ is larger than that under the condition of positive returns $\hat{\rho}^+(c)$. This means that the sample downside correlations are greater than the upside ones. That is, the spot and futures markets co-moved more often when markets went up than when the markets went down. The $p$-values of test statistics of asymmetries are all larger than 10%, even larger than 50% indicating that we cannot reject the null hypothesis of no asymmetric correlations. That is to say, the exceedance correlations between spot and futures returns were statistically symmetric. Moreover, for returns series of spot and futures contract with larger maturity, the $p$-value is smaller indicating that the degrees of correlation symmetries were weaker with the larger maturity of futures contract.
The general analysis cannot reveal the dynamics of local situations. We use the method of rolling sample test which has been widely used to investigate many topics on crude oil markets, such as market efficiency [14,16,17] and modeling evaluation [41–44]. For various purposes, the fixed length of rolling windows should be determined by caution. In this paper, we study the dynamics of short-term asymmetric correlations, if the window length is too large, caused by the seasonal factors and economic cycling, the calculated statistics may lose the locality and cannot reflect the evolution of short-term situations. Thus, following Wang et al. [51,52], we set the window length is 250 business days, about one year. We use the first 250 observations of spot and futures returns, calculate the exceedance correlations, roll the sample one point forward eliminating the first observation and including the next one in each series, and repeat this procedure until the end of the series. We show the evolution of exceedance correlations in Fig. 3 with window rolling. The time labeled in x-axis is the date of the last day in each window.

In Fig. 3, we can find that the conditional correlations generally became higher and higher over time. With the window moving, the exceedance correlation coefficients abruptly became very low during some periods, such as 1991–1992, 1996–1998. We can relate these evidences to some occasional events. From 1991 to 1992, caused by Iraq’s invasion on Kuwait and the following Gulf War, the shocks on oil supply made the fact that the spot oil prices did not be in accordance with people expectation which was an important determinant of futures prices. Thus, the conditional correlations became very low. While during 1996–1998, the unexpected Asian financial crisis made an essential impact on Asian economies and brought the shock on oil demand which break the high correlations. The conditional correlations also became very low.

### Table 3

The exceedance correlations between return series of WTI spot and futures prices.

<table>
<thead>
<tr>
<th>Threshold value</th>
<th>Spot and WTI F1</th>
<th>Spot and WTI F2</th>
<th>Spot and WTI F3</th>
<th>Spot and WTI F4</th>
</tr>
</thead>
<tbody>
<tr>
<td>−3</td>
<td>0.9857</td>
<td>0.9513</td>
<td>0.9554</td>
<td>0.9533</td>
</tr>
<tr>
<td>−2.5</td>
<td>0.9661</td>
<td>0.9371</td>
<td>0.9198</td>
<td>0.9200</td>
</tr>
<tr>
<td>−2</td>
<td>0.9565</td>
<td>0.9021</td>
<td>0.8933</td>
<td>0.8852</td>
</tr>
<tr>
<td>−1.5</td>
<td>0.9486</td>
<td>0.8774</td>
<td>0.8731</td>
<td>0.8648</td>
</tr>
<tr>
<td>−1</td>
<td>0.9281</td>
<td>0.8780</td>
<td>0.8681</td>
<td>0.8605</td>
</tr>
<tr>
<td>−0.5</td>
<td>0.8763</td>
<td>0.8383</td>
<td>0.8507</td>
<td>0.8238</td>
</tr>
<tr>
<td>0</td>
<td>0.8903</td>
<td>0.8512</td>
<td>0.8345</td>
<td>0.8131</td>
</tr>
<tr>
<td>0+</td>
<td>0.8874</td>
<td>0.8169</td>
<td>0.8028</td>
<td>0.7928</td>
</tr>
<tr>
<td>0.5</td>
<td>0.8730</td>
<td>0.7597</td>
<td>0.7371</td>
<td>0.7208</td>
</tr>
<tr>
<td>1</td>
<td>0.8811</td>
<td>0.7001</td>
<td>0.6713</td>
<td>0.6785</td>
</tr>
<tr>
<td>1.5</td>
<td>0.8663</td>
<td>0.5845</td>
<td>0.6150</td>
<td>0.5947</td>
</tr>
<tr>
<td>2</td>
<td>0.8460</td>
<td>0.5375</td>
<td>0.5015</td>
<td>0.3662</td>
</tr>
<tr>
<td>2.5</td>
<td>0.7603</td>
<td>0.2160</td>
<td>0.2865</td>
<td>0.3752</td>
</tr>
<tr>
<td>3</td>
<td>0.8219</td>
<td>0.3011</td>
<td>0.5053</td>
<td>0.4880</td>
</tr>
<tr>
<td>p-value</td>
<td>0.9846</td>
<td>0.6189</td>
<td>0.6426</td>
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</tbody>
</table>
We show the evolution of test statistics and the critical value at 1% significant level in Fig. 4. The exceedance level $c$ is set to be 0, 0.5, 1, and 1.5 because for some larger exceedance level $c'$, there was no standard return larger than $c'$ or smaller than $-c'$ for the sub-series in some windows. For spot and “WTI F1”, the test statistics were all smaller than the critical values. However, for spot and the other three contracts, we can find that the test statistics were larger than the critical value during some periods, such as 1991–1992, 1996–1998 and 2008–2009 which can be related to the Gulf War, Asian financial crisis and the recent global economic depression, respectively. That is, some occasional events could cause the asymmetries of the exceedance correlations between spot and futures returns.

4.2. The cross-correlations

We provide the log–log plots of cross-correlation statistics $Q_{cc}(m)$ versus lagged order $m$ in Fig. 5 with $m$ (also the degree of freedom) varying from 1 to 1000. As a comparison, we also show the critical values for the $\chi^2(m)$ distribution at the 5% level of significance in Fig. 4.

We can find that most of the lagged cross-correlation statistics $Q_{cc}(m)$ are smaller than the critical values when the lagged order $m$ is smaller than 5. For $m$ larger than 5, even for $m$ larger than $10^2$, the statistics $Q_{cc}(m)$ are larger than the critical value. Thus, we can reject the null hypothesis of no long-range cross-correlations indicating that the long-range cross-correlations between spot and futures returns were significant at 5% level.

Quantitatively, based on DCCA proposed by Podobnik and Stanley [19], we provide the log–log plots of $F(s)$ versus time scale $s$ in Fig. 6. The slopes of regression lines, just the scaling exponents are also labeled in Fig. 6. We can find that the scaling exponents are larger than 0.5 but are very near to 0.5 indicating that the cross-correlations between spot and futures returns are weakly persistent (positive). The reason is that the variations of futures prices partly determine the long-term trend of spot prices in the futures. Thus, the cross-correlations were positive. Interestingly, the scaling exponents increase with the maturity of futures contract increasing implying that the long-range cross-correlations between returns of spot and futures with larger maturity are stronger. For the futures with a larger maturity, the prices affect the longer-term trend of spot prices. As a performance, the long-range cross-correlations are stronger.

As a rolling sample test, Fig. 7 reports the evolution of scaling exponents with window rolling. In Fig. 6, the cross-correlations evolved erratically. The scaling exponents sometimes were larger than 0.5, e.g., during the period 1993–1995 and 2003–2005. Sometimes, the scaling exponents were smaller than 0.5 implying the cross-mean-reversion behavior, e.g., during the period 1991–1993 and 2008–2009 which can be related to the Gulf crisis and the recent global economic depression. Overall, the scaling exponents were much closer to 0.5 in the recent than at the beginning of 1990s implying the weaker cross-correlations. We can partly attribute the fact to the more efficient operation of the crude oil markets.
5. Some implications

5.1. Relationship between spot and futures markets of crude oil

In this paper, we focus on the exceedance correlations and cross-correlations between crude oil spot and futures markets employing several nonparametric methods. Although the results cannot reject the null hypothesis of symmetries, the evidence from rolling sample technique indicates that the asymmetries of exceedance correlations were significant at the 1% level sometimes. Moreover, the results based on detrended cross-correlation analysis (DCCA) show that the cross-correlations between spot and futures markets were nonlinear (fractal), which further asserts the nonlinear structure in the correlations between two markets. Thus, for empirical analysis, the nonlinear models or methods should be more appealing.
5.2. The influence of the exogenous events

Our rolling sample results show that some essential events could produce the asymmetries of the exceedance correlations and make the evolution of the cross-correlations become more volatile. Wang and Liu [17] and Alvarez-Ramirez et al. [18] both indicated that the short-term structure of crude oil markets is mainly dominated by market exogenous factors such as geopolitical events and extreme climate. In fact, the effects of the occasional events on the microstructure of financial markets have been investigated extensively. The evidence of exogenous events on market statistical property can be found in several recent papers [45,24,25]. For example, Podobnik et al. [24] revealed pronounced peaks in volatility cross-correlations during the largest market shocks and economic crisis: the Black Monday, the Dot-com Bubble, and the 2008 crash, by employing time lag random matrix theory (RMT). Precisely, the pronounced peaks were found for the longest $N = 88$ members of the S&P 500 index the largest RMT singular value versus year. Besides, the Podobnik et al. [24] reported power-law volatility cross-correlations between the return series of the NYSE Composite members. The same volatility cross-correlations were reported recently in Wang et al. [25] among the worldwide financial indices. Especially for crude oil markets, Zhang et al. [46] estimated the impact of extreme events on crude oil price using an EMD-based event analysis method and found the impacts of Persian Gulf War in 1991 and the Iraq War in 2003. From an event study perspective, Demirer and Kutan [47] found the significant impacts of OPEC conference and Strategic Petroleum Reserve (SPR) announcements on the returns of crude oil spot and futures prices. Lee et al. [48] found that the permanent component of conditional variance increased with the occurrence of a sudden major event employing a Component-ARJI model with structural break analysis. Our results in this article indicate that the extreme events could affect the asymmetries of
exceedance correlations and cross-correlations between spot and futures markets which further confirm the evidence of previous works. Thus, modeling the dynamics of crude oil markets should consider the factor of structural break caused by exogenous events and regime switching.

5.3. The predictability and market efficiency

Employing DCCA method, we find that the spot and futures returns were weakly long-range cross-correlated, and the cross-correlations were also significant based on the analysis of a statistic. Moreover, the rolling sample results indicate that the cross-correlations were time varying. That is, one can improve the predictability of the spot (futures) prices based on the history data of futures (spot) prices during a certain period. Overall, the cross-correlations were weaker and weaker indicating that the predictability was also weaker and weaker over time. Additionally, for a pure efficient market, the prices cannot be predicted based on the technical analysis of history prices. Then, if the crude oil markets were efficient, the spot (futures) returns were not auto-correlated. Theoretically, the futures price is the unbiased estimation of future spot price. Thus, spot and futures returns are not cross-correlated under the efficient market hypothesis. Previous works on crude oil market efficiency mainly focused on the auto-correlations based on the rescaled range analysis [12,14], detrended fluctuation analysis [16], multiscale analysis [17], lagged DFA [18], and so on. Our evidence from cross-correlations also implies that the crude oil markets were inefficient, but were more efficient recently than at the beginning of 1990s, and some exogenous events could affect the degree of market efficiency (Fig. 7).

5.4. The heterogeneity of the crude oil markets

As argued in Corsi [49], a financial market is composed of participants having a very large spectrum of trading frequency. At the one end of the spectrum there are the dealers with very short trading horizon and high frequency. At the other end, there are institutional investors such as pension funds with very low trading frequency and long horizon. As one of the important reasons of the market heterogeneity in Müller et al. [50], the difference of market behavior in the various trading horizons can imply the characteristic of heterogeneity. Our results suggest that the various significance of lagged correlations between smaller lagged order (smaller than a week) and larger order (larger than a week) which can be considered as the results of the operation of diversified investors with various trading horizons.

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**Fig. 7.** Dynamics of scaling exponents with window moving.
5.5. The rolling sample test

There are multitudes of papers which employ the rolling sample test to analyze financial market dynamics [14,16,51–54]. The rolling sample test can provide additional insights in the evaluation of time series dynamics. First, from the analysis of rolling sample, one can get the evolutions of statistical property of time series [14,53,54]. For example, Cajueiro and Tabak [53] found that emerging markets were becoming more efficient over time based on the rolling sample test of long-range dependence. Cajueiro and Tabak [54] also employed rolling sample test to examine the long-range dependence of the volatility series in emerging markets and their evidence supported that emerging markets were more and more efficient. The similar analysis can also be found in the analysis of crude oil market efficiency [14]. Second, using the rolling sample test, one can find out the possible effects of exogenous events on market dynamics [51,52,16]. For example, Wang et al. [51] found that a price-limited reform can affect cross-correlations among Chinese stock markets. Wang et al. [52] also found the effects of an announcement on gold market efficiency and multifractality. Alvarez-Ramirez et al. [16] used rolling sample test to examine the auto-correlations in crude oil returns and found the shocks of several events on short-term market efficiency.

On the application of rolling sample test to financial markets, the selection of window size should be cautious. In this paper, we set the window size to be 250 business days, about a year. This window size can be seen in Wang et al. [51,52]. For large window size, the evolution of statistic property (scaling exponents) is smoother and the major trend can be easily found. But for large window size, the effects of some events on market short-term dynamics are covered. Caused by the seasonal factors and economic cycling, the calculated statistics may lose the locality and cannot reflect the evolution of short-term situations. For small window size, the change of scaling exponents is fiercer. Thus, the long-term trend of market dynamics is disturbed by the short-term noise. In this perspective, to analyze the general trend of long-term market dynamics, such as market efficiency, one should choose large window size, rather than small window size [14,53,54]. To analyze the effects of exogenous events on market short-term dynamics, small window size is the better choice [16,51,52].

6. Conclusion

In this paper, we first study the asymmetric property of exceedance correlations between return series of WTI spot and four futures contract prices. We find that spot and futures returns are power-law distributed. Moreover, our finding shows that the sample downside correlations were greater than the upside ones. Employing the non-modeling test proposed by Hong et al. [36], our results cannot reject the null hypothesis of symmetric correlations indicating that the exceedance correlations between return series of spot and futures prices were symmetric. The degrees of symmetries were lower for the correlations between spot and futures contract with larger maturity. Employing a rolling sample test, we can find that some exogenous events such as the Gulf War and financial crisis could make apparent effects on the asymmetries of the exceedance correlations. Then, we also test the cross-correlations between return series of spot and four futures contracts. Qualitatively, using a statistical test in analogy to the Ljung–Box test, we find that the cross-correlations were significant at the 5% level, even for the lagged order larger than $10^2$, indicating that the spot and futures returns were significantly long-range cross-correlated. Quantitatively, employing DCCA method, we find that the cross-correlations were all weakly persistent and were stronger for those between the spot and the futures contract with larger maturity. The results from rolling sample test suggest that the cross-correlations could be affected by some occasional events. The recent cross-correlations were weaker than those at the beginning of 1990s. We also have some discussions relevant to our results of the exceedance correlations and cross-correlations.

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References


