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Revisiting the relationship between spot and futures oil prices: Evidence from quantile cointegrating regression

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A B S T R A C T

Since most real decisions depend upon current market states or whether it is advantageous to the participants themselves, this paper revisits the relationship between spot and futures oil prices of West Texas Intermediate covering 1986 to 2009 with an innovative approach named quantile cointegration. Different to previous perspectives, we target the issues of cointegrating relationships, causalities, and market efficiency based on different market states under different maturities of oil futures. In our empirical analysis, except for market efficiency, long-run cointegrating relationships and causalities between spot and futures oil prices have significant differentials among futures maturities and the performances of spot oil markets. Furthermore, the response of spot prices to shocks in 1-month futures oil prices is much steeper in high spot prices than in low spot prices. This phenomenon is consistent with the prospect theory (Kahneman and Tversky, 1979), in that the value function is generally steeper for losses than for gains.

1. Introduction

There exist many studies on energy markets discussing the asymmetric effects of oil shocks on economic activities or financial markets (Huang et al., 2005; Park and Ratti, 2008; Kilian, 2008, for example). Borenstein et al. (1997) and Lardic and Mignon (2006) explore that the possible sources of non-linearity for energy prices are monetary policy, adjustment costs, adverse effects of uncertainty on the investment environment, sellers' market power, production/inventory adjustment lags, and asymmetry in oil product price. The responses of market participants to oil prices shocks are not perfectly significantly rational. Samuelson and Zeckhauser (1988) state that:

"*To do nothing is within the power of all men*."

In other words, according to the status quo, it is sometimes better to do nothing than to adopt other decisions. We cannot expect market participants to be rational in the face of several kinds of situations, especially quite extreme situations. The prospect theory (Kahneman and Tversky, 1979) indicates that people tend to overweight losses with respect to comparable gains and engage in risk-averse behavior with respect to gains and risk-acceptant behavior with respect to losses. People thus respond to probabilities in non-linear (or asymmetric) manners.

Some studies do discuss causalities between spot and futures oil prices with non-linear methods (Bekiros and Diks, 2008; Huang et al., 2009). Others examine the efficiency of crude oil markets conditional on some episodes of extreme volatility (Moosa and Al-Loughani, 1994; Switzer and El-Khoury, 2007, for example). What the large numbers of non-linear methods emerge for are mainly relative to tests and prediction. For example, Michael et al. (1997) argue that non-linearity could lead to non-rejection of the null hypothesis of no cointegration. Nevertheless, Tversky and Kahneman (1991) propose a reference-dependent theory of consumer choice, which explains such effects by a deformation of indifference curves about the reference point. The asymmetry of gains and losses around a reference point means how people identify the reference point and hence how they frame a choice issue can have a critical effect on their choices. In fact, under real decisions, recent market performance always impacts the sentiments of consumers or investors, especially when markets are in a clear trend (e.g., a bull or a bear market).

This paper contributes to the existing literature in the following. First, we apply the interesting view of the prospect theory to re-examine the relationship between spot and futures oil prices with an advanced quantile cointegrating regression (QC hereafter) developed by Xiao (2009) under different market states and different maturities of futures oil prices. Our empirical results support the non-linear

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cointegration between contemporaneous spot and futures oil prices with daily data among futures contracts with different maturities. Differently, we find that the long-run relationship between spot and futures oil prices varies according to not only the contract lengths of futures oil prices, but also the reference points-current performances of spot crude oil markets. Moreover, we also examine the effect of error-corrections (EC, hereafter) — that is, explore the estimated coefficients of error-correction terms across various quantiles, rather than a constant coefficient as in conventional linear methods. In fact, our empirical results present the differentials among various quantiles.

Second, our empirical results support bi-directional causalities between spot oil prices and 1-month futures oil prices across all quantiles. However, the results of uni-directional causalities or bi-directional causalities are found only in some quantiles and long futures contracts (2-, 3-, and 4-months). Current market states could affect the lead–lag relation between spot and futures oil prices. Finally, the efficient market hypotheses are supported in short futures contracts, and the efficiency in crude oil markets seems to be satisfied easily with the no arbitrage rule. Here, we employ the prospect theory to explain these phenomena discussed in the next section.

The remainder of this paper is organized as follows. Section 2 presents a literature discussion from a conceptual economic perspective relative to our works. Section 3 describes the data information. Section 4 gives empirical models and empirical methodologies. Section 5 offers the empirical analysis and the implications of the results. The final section shows the conclusions.

2. Literature discussions

There exist many studies exploring the linkage of spot and futures prices for predictability, market efficiency, and cointegration.[1] Some works find that spot and futures price are not cointegrated, or they are cointegrated, but do not move together one-for-one in the long run. Recent studies focus on investigating the non-linear causality between spot and futures oil markets (Bekiros and Diks, 2008; Huang et al., 2009). It is a pity that long-run cointegration relationships are still limited to be constant in the methods used by those existing studies. Although one recent developed methodology called time-varying cointegration[2] solves this problem, the impact of current market states in that model is limited to further considerations. To fill this gap, the current paper employs the advanced developed method — named the quantile cointegration approach. This method allows us to discuss cointegrating relations between spot and futures oil prices based on the performances of spot oil prices.[3] In contrast to the traditional linear estimation of cointegration conditions on the mean distribution of the dependent variable, this method allows us to explore the time-varying coefficients in the cointegrating relationship conditions on the quantile of a dependent variable's distribution.

Why should we notice the non-linear effects for spot–futures oil prices? Before discussing about irrational performances found in recent studies, let us recall one experiment shown in the prospect theory (Kahneman and Tversky, 1979).

Condition 1.
Case A: You will gain \$4000 with probability 0.8.
Case B: You will gain \$3000 with probability 1.

Condition 2.
Case C: You will lose \$4000 with probability 0.8.
Case D: You will lose \$3000 with probability 1.

Which one will you choose for each condition? Do you choose them rationally? In their experiments, Case B is the prevalent preference for Condition *1*, and Case C is the prevalent preference in Condition *2*. These results are not inconsistent with expected utility theory. The expected utility in Condition *1* is \$3200, which is more than in Case B, but people choose chase for a sure gain. However, when people face a sure loss, they are transformed into risk seekers. Obviously, they have different attitudes in facing gains and losses. More importantly, according to their findings, their responses to losses are much steeper than to gains.

According to the prospect theory, economic agents are concerned about changes in wealth rather than with its final state. An economic agent feels more pain with a loss than he feels happy with a gain that is of the same size of the loss. Kahneman and Tversky (1979) find that the preference between negative prospects is the mirror image of the preference between positive prospects. They label this pattern as the reflection effect. Moreover, they show that people become more willing to take risks to avoid losses than to realize gains. These observations illustrate what is often called the loss aversion attitude.

In empirical works such evidence can be found in some areas. For example, Mascarenhas and Aaker (1989) present that firms adjust their strategies significantly and asymmetrically over business cycle stages. Genesove and Mayer (2001) explain the positive price–volume relationship from the perspective of loss aversion that sellers are irrationally averse to realizing losses in depressing markets. These results exhibit the effects of market states on real decision-making. Advantageous and disadvantageous conditions will produce differential reactions. In addition, there exist perspectives for explaining non-linearity and its necessity. For example, Maslyuk and Smyth (2008) find that each oil price series can be characterized as a random walk process and that structural breaks are significant and meaningful in terms of events that have impacted world oil markets. Moreover, Maslyuk and Smyth (2009a) obtain the characteristics of a non-linear process in crude oil production. With this finding, conventional unit-root tests, which assume linear and systematic adjustment, could interpret a departure from linearity as being permanent stochastic disturbances. These findings stress the influences of exogenous shocks that cause non-linearities.

No previous study has allowed for quantile-varying in a cointegrating vector. In the spot–futures markets, if relationships between spot and futures prices do not approach equilibrium, then an effect such as arbitrage or speculation will make it equilibrium.[4] Abhyankar (1996) shows the non-linear relationship can be ascribed to the difference in transaction costs, the microstructure effects of the market, or the role of noise traders. Other potential sources of the non-linearity include diversity in agents' beliefs (Brock and LeBaron, 1996), herd behavior (Lux, 1995), oligopolistic and monopolistically competitive markets (varying degrees of price rigidity; Galeotti et al., 2003), and heterogeneity in investors' objectives (Peters, 1994). While we acknowledge the potential importance of time-varying effects, it is this kind of non-linearity that inspires us to continue the research in this paper.

In energy markets the long-run cointegration relationship between spot and futures oil prices has been proven. Some studies utilize conventional linear cointegration, such as the methods of Engle

[1] For example, see Bopp and Sitzer (1987), Serletis and Banack (1990), and Crowder and Hamed (1993) for the early literature, and McAleer and Sequeira (2004), Cologni and Manera (2008), and Maslyuk and Smyth (2009b) for the recent literature.

[2] Chow (1998) employs a Markov regime switching framework and shows that tests for cointegration and estimates of the cointegrating vector are likely to be biased when a sample contains infrequent changes in regime. Taking these shifts into account, the null hypothesis that spot and futures prices are cointegrated and move together one-for-one in the long run no longer can be rejected.

[3] Cointegration, in simple words, refers to co-movements of variables in the long run. Economic theory does not show that the cointegration relationship must be linear. Instead, it predicts three possibilities for the relationship: cointegration, non-linear cointegration, and no cointegration (Zhou, 2010).

[4] Please see Moosa and Al-Loughani (1995) who discuss this related issue.

and Granger (1987) and Johansen (1988), to examine the long-run equilibrium between spot and futures oil prices (For example, Quan, 1992; Schwartz and Szakmary, 1994; Silvapulle and Moosa, 1999; McAleer and Sequeira, 2004). Recent studies equipped with non-linear models, however, only discuss the potential non-linear adjustment mechanisms about deviating from the long-run equilibrium relationships for spot and futures oil markets (Ewing et al., 2006; Bekiros and Diks, 2008; Huang et al., 2009, for example). The limitation of time-invariant cointegrating coefficients in their estimation implies a constant long-run relation, rather than a sequence of cointegrating relations varying with time or innovations of markets. This paper employs quantile cointegrating regressions to estimate the long-run relation between spot and future oil prices conditional on market innovations.

Some recent studies examine the lead–lag relation between spot and futures oil prices, in which they compare the difference between the results of linear and non-linear methods. For example, Silvapulle and Moosa (1999) show that linear causality testing reveals that futures prices lead spot prices, but non-linear causality testing shows a bi-directional relationship. Bekiros and Diks (2008) offer that pair-wise vector error-correction models (VECM) suggest a strong bi-directional Granger causality between spot and futures oil prices, but non-linear methods present a uni-directional causality under some restricted conditions. Different from the usage of non-linear methods, Bopp and Sitzer (1987) test the predictability of futures prices to spot prices in heating oil markets. They find that near-term futures prices add information to the forecasting process, but futures prices more than 3 periods out do not.

Some studies discuss the efficiency of crude oil markets. Crowder and Hamed (1993) find the non-rejection of the speculative efficiency hypothesis with New York Mercantile Exchange (NYMEX) crude oil contracts during the period 1983–1990. Moosa and Al-Loughani (1994) suggest that futures oil prices (WTI) are neither unbiased nor efficient forecasters of spot prices during the period 1986–1990. Peroni and McNown (1998) support the speculative efficiency hypothesis for West Texas Intermediate (WTI) oil prices during the period 1984–1996. Switzer and El-Khoury (2007) examine the efficiency of the oil market (NYMEX) and support market efficiency, even during episodes of extreme conditional volatility. Obviously, they see episodes with extreme volatility may possibly influence market efficiency. This paper examines market efficiency from the perspectives of various market state performances.

After reviewing the above existing studies, we conclude that more and more detailed and precise examinations have been exerted since the exposure of a deviation in estimating or predicting using conventional methods. Therefore, to improve the deviation and to match what happens under real decisions, we employ quantile cointegrating methods to examine the cointegration, causalities, and market efficiency in spot–futures oil markets.[5]

3. Data

This paper investigates the relationship between spot and futures prices in crude oil markets. The time-series data we adopt consist of the daily spot and futures oil prices of West Texas Intermediate (WTI) covering January 2, 1986 to July 6, 2009. The source of the data is from Energy Information Administration (EIA). The futures oil prices include four kinds of contracts in maturity, i.e. 1, 2, 3, and 4 months, which are traded on the New York Mercantile Exchange (NYMEX).

Each contract expires on the third business day prior to the 25th calendar day of the month proceeding the delivery month. If the 25th calendar day of the month is a non-business day, then trading ceases on the third business day prior to the business day preceding the 25th calendar day. Table 1 shows the descriptive statistics and correlations of spot and futures oil prices, where *LnS*, *LnF1*, *LnF2*, *LnF3*, and *LnF4* denote the forms of natural logarithm for spot prices and the four kinds of futures prices maturing in 1, 2, 3, and 4 months, respectively. Table 1 presents that correlations between spot and four kinds of futures oil prices are close to one — that is, the movements of spot and futures oil prices are close. On the other hand, by the Jarque-Bera (Jarque and Bera, 1980) test, we confirm the non-normality of variables, therefore revealing the appropriateness and necessity of quantile regressions, which improve non-normal skewness and kurtosis in estimation.

4. Methodology

In our empirical processes we mainly conduct an examination through the following steps. First, we test the stationarity of variables with several kinds of unit-root tests. Second, we apply Johansen's linear cointegration model to examine whether the cointegrating relationship exists or not. Third, we test the null hypothesis of constant cointegrating coefficients by using bootstrapped critical values and further analyze with quantile cointegrating regressions. Finally, we test causalities between spot and futures oil prices with linear, non-linear, and quantile methods. We mainly explore three critical issues: (i) contemporaneous spot and futures oil prices; (ii) the lead–lag relation between spot and futures oil prices; (iii) efficient market hypotheses in crude oil futures markets.

4.1. Models

In testing the unit root we apply the Augmented Dickey-Fuller (1979) (ADF), Phillips-Perron (1988) (PP), and Kwiatkowski et al. (1992) (KPSS) tests. For a detailed review about these unit-root tests, one can see Maddala and Kim (1998). In testing the effect of cointegration, we apply Johansen's cointegration methodology developed by Johansen (1991, 1995). This method tests with linear cointegrating regressions restricted in a VAR representation. To save space, please see details in Johansen (1995).

The concept of cointegration is mainly applied for non-stationary time series variables that produce stationary residuals in models. We employ the quantile cointegrating regression developed by Xiao (2009) to examine contemporaneous spot and futures oil prices. To avoid endogeneity,[6] Xiao adopts the approach proposed by Saikkonen (1991), who uses leads and lags to deal with endogeneity in the traditional cointegration model.[7] The equation is as follows:

$$LnS_t = \alpha + \beta LnF_t + \sum_{i=-K}^{K} \omega_i \Delta LnF_{t-i} + \varepsilon_t, \tag{1}$$

where *LnS* is a spot oil price taken in natural logarithm, *LnF* is a futures oil price taken in natural logarithm, and ε denotes a residual. The number K is the length of the lead–lag terms. Here, we set K to be three.[8] In empirical works, we replace *LnF* with *LnF*1, *LnF*2, *LnF*3, and *LnF*4 for different contracts and the following equations go along with this setting.

[5] The literature about market efficiency (e.g., Crowder and Hamed, 1993) between spot and futures oil markets will be described in an empirical analysis.

[6] Indeed, in our Granger-causality test a bi-directional relationship appears between the two variables (see panel A of Table 7).

[7] In deciding the kinds of trend terms, we adopt the Akaike Information Criteria (AIC) in testing Johansen's cointegration models. According to AIC, the model with an intercept but no time trend is appropriate. The relative discussion can be seen in Pesaran and Smith (1998).

[8] We also set K to be 7 and 30, respectively, but it does not show much difference between them.

Table 1
Descriptive statistics and correlation matrix.

	LnS	*LnF*1	*LnF*2	*LnF*3	*LnF*4
Descriptive statistics					
Maximum	4.98	4.98	4.98	4.98	4.99
Minimum	2.33	2.34	2.36	2.36	2.37
Skewness	1.05	1.05	1.07	1.10	1.13
Kurtosis	3.29	3.29	3.27	3.28	3.30
Jarque-Bera	1087.7	1091.5	1141.6	1202.6	1268.8
Probability	0.00	0.00	0.00	0.00	0.00
Observations	5846	5846	5846	5846	5846
Correlation matrix					
LnS	1.000	–	–	–	–
*LnF*1	0.999	1.000	–	–	–
*LnF*2	0.998	0.999	1.000	–	–
*LnF*3	0.996	0.997	1.000	1.000	–
*LnF*4	0.994	0.995	0.998	1.000	1.000

By testing Granger causality, we are able to decide the role of the lead–lag variables. Here, we use the following equation to test the Granger causality between variables.

$$\Delta LnS_t = \alpha + \eta\hat{\varepsilon}_{t-1} + \sum_{i=1}^{N} \beta_i \Delta LnF_{t-i} + \sum_{j=1}^{M} \gamma_j \Delta LnS_{t-j} + e_t \qquad (2)$$

$$\Delta LnF_t = \alpha + \eta\hat{\varepsilon}_{t-1} + \sum_{i=1}^{N} \beta_i \Delta LnF_{t-i} + \sum_{j=1}^{M} \gamma_j \Delta LnS_{t-j} + e_t, \qquad (3)$$

where Δ denotes the first difference of variables, and N and M are the lag lengths. The variable $\hat{\varepsilon}_{t-1}$ is the 1-lagged variable of the estimated error-correction terms given from Eq. (1), and e_t denotes a residual. In our empirical work, we set N and M as the same and choose them with Schwarz information criteria (SIC) in vector auto-regression (VAR) models.

In testing the efficiency of the spot and futures oil markets, we adopt the expectations hypothesis and the no arbitrage rule.[9] Under risk neutrality, the expectations hypothesis implies the following model:

$$LnS_t = \alpha + \beta LnF_{t-M} + \sum_{i=-K}^{K} \omega_i \Delta LnF_{t-i} + \varepsilon_t, M = 1,2,3,4, \qquad (4)$$

where ε is the residual. We also implement the lead–lag terms ΔLnF_{t-i} ($i = -K$ *to* K) to deal with the endogeneity, where K is three. This model is based on the definition of market efficiency that argues futures prices, LnF_{t-M}, should contain all relevant information in forecasting the next period's spot prices, LnS_t. The joint restrictions of market efficiency and risk neutrality imply values of $\alpha = 0$ and $\beta = 1$. This is the same as Fama's (1970) notion of weak form efficiency.

The condition of the no arbitrage rule derived by Brenner and Kroner (1995) describes that investors should be indifferent between owning an open spot position and selling the futures price, or for purchasing a risk-free bond that matches the maturity of the futures contract. The lead-lag terms are adopted to avoid endogeneity. Thus, this condition implies the following model:

$$LnS_t = \alpha + \beta_1 LnF_{t-M} + \beta_2 R_t + \sum_{i=-K}^{K} \omega_i \Delta LnF_{t-i} + \sum_{j=-L}^{L} \psi_j \Delta R_{t-j} + \varepsilon_t, M = 1,2,3,4, \qquad (5)$$

where R is the continuously compounded rate of return on risk-free bonds, i.e., $R = \ln(1+r)$ with the interest rate r of risk-free bonds[10] and the length of lead–lag terms ΔLnF_{t-i} and ΔR_{t-j} (we set $K = L = 3$). Here, the constant term is not required to be zero, but it is necessary to jointly restrict the conditions $\beta_1 = 1$ and $\beta_2 = 1$. Error terms should be serially uncorrelated for market efficiency. We adopt monthly data to test the market efficiency under the expectations hypothesis and the no arbitrage rule.

4.2. Quantile cointegrating regression

In contrast to traditional linear cointegration models, many applications in financial and economic areas suggest that the cointegrating vector might not be constant. On the one hand, Park and Hahn (1999) apply the cointegration model with time-varying coefficients, where the coefficient is a function of a deterministic time trend. Differently, Xiao (2009) considers the cointegration model whereby the cointegrating coefficient is affected by innovations. We introduce the quantile cointegrating model briefly and further detailed discussion can be seen in Xiao (2009).[11]

The traditional cointegration model describes that:

$$y_t = \alpha + \beta_t' x_t + u_t, \qquad (6)$$

where y_t and x_t are integrated with order 1 ($I(1)$), and u_t is stationary in level. To extend traditional cointegration models, Xiao (2009) applies the idea proposed by Saikkonen (1991) that decomposes u_t into the lead–lag terms $\sum_{j=-K}^{K} \Delta x_{t-j}$ and a pure innovation component ε_t to deal with endogeneity in traditional cointegration models. This is described in the following model:

$$y_t = \alpha + \beta_t' x_t + \sum_{j=-K}^{K} \Delta x_{t-j}' \Pi_j + \varepsilon_t. \qquad (7)$$

[9] Cointegrating the oil price pairs of Eq. (1) does not necessarily mean that futures markets present efficiency or inefficiency (Maslyuk and Smyth, 2009b).

[10] The interest rate we use is the 3-month Treasury bond, and the data source is *Datastream*.

[11] Compared to the quantile regression approach, other possible non-linear methods such as threshold autoregressive (TAR) or Markov switching are not able to estimate conditional quantiles, because they were originally proposed to investigate non-linear models for conditional means (Lima et al., 2008).

If we denote the τ-th quantile of ε_t as $Q_\varepsilon(\tau)$ (let$\Im_t = \sigma\{x_t, \Delta x_{t-j}, \forall j\}$), then conditional on $\Im_t$, the τ-th quantile of y_t is given by:

$$Q_{y_t}(\tau|\Im_t) = \alpha + \beta(\tau)'x_t + \sum_{j=-K}^{K} \Delta x'_{t-j}\Pi_j + F_\varepsilon^{-1}(\tau), \quad (8)$$

where $F_\varepsilon(\cdot)$ is the c.d.f. of ε_t. Let Z_t be the vector of regressors consisting of $(1,x_t)$ and $(\Delta x'_{t-j}, j=-K,\cdots,K)$, $\Theta=(\alpha,\beta'_t,\Pi'_{-K},\cdots,\Pi'_K)'$, and:

$$\Theta(\tau) = \left(\alpha(\tau), \beta(\tau)', \Pi'_{-K}, \cdots, \Pi'_K\right)', \quad (9)$$

where $\alpha(\tau)=\alpha+F_\varepsilon^{-1}(\tau)$. We then rewrite the above regression as:

$$y_t = \Theta' Z_t + \varepsilon_t \quad (10)$$

and

$$Q_{y_t}(\tau|\Im_t) = \Theta(\tau)'Z_t. \quad (11)$$

If we set $\varepsilon_{t\tau}=\varepsilon_t - F_\varepsilon^{-1}(\tau)$, then $Q_{\varepsilon_{t\tau}}(\tau)=0$. In the above model, the cointegrating coefficients β_t are affected by innovations received at each period. Consequently, the cointegrating vector can vary over the quantiles and thus may be quantile τ-dependent. The conditioning variables not only shift the location of the distribution of y_t, but also may alter the scale and shape of the conditional distribution.

Another further problem examines whether the cointegrating vector β_t is constant or not. The main test is conducted under the hypothesis $H_0:\beta(\tau)=\overline{\beta}$ over all quantiles (τ), where $\overline{\beta}$ is a vector of unknown constants. A natural preliminary candidate for testing constancy of the cointegrating vector is a standardized version of $\left(\widehat{\beta}(\tau)-\overline{\beta}\right)$, where $\hat{\beta}(\tau)$ is the estimator of $\beta(\tau)$. Under the null and sample size n:

$$n\left(\widehat{\beta}(\tau)-\overline{\beta}\right) \Rightarrow \frac{1}{f_\varepsilon\left(F_\varepsilon^{-1}(\tau)\right)}\left[\int_0^1 \underline{B}_{\Delta x}\underline{B}_{\Delta x}^T\right]^{-1}\int_0^1 \underline{B}_{\Delta x} dB_\Psi^*, \quad (12)$$

where $f(\cdot)$ and $F(\cdot)$ are respectively the p.d.f. and c.d.f. of u_t in Eq. (6), $\Psi_\tau(u)=\tau-I(u<0)$ for indicator I, $\underline{B}$ is the demeaned Brownian motion, $B_\psi{}^*(\cdot)$ is the Brownian motion independent with $B_{\Delta x}(\cdot)$, and "$\Rightarrow$" represents weak convergence of the associated probability measures. Denote $\hat{\beta}$ as a preliminary estimator of $\overline{\beta}$.

We now look at the process $\hat{V}_n(\tau) = n\left(\hat{\beta}(\tau)-\hat{\beta}\right)$. Under H_0:

$$\hat{V}_n(\tau) \Rightarrow \frac{1}{f_\varepsilon\left(F_\varepsilon^{-1}(\tau)\right)}\left[\int_0^1 \underline{B}_{\Delta x}\underline{B}_{\Delta x}^T\right]^{-1}\int_0^1 \underline{B}_{\Delta x} dB_\Psi^* - \text{plim}\, n\left(\hat{\beta}-\overline{\beta}\right), \quad (13)$$

which depends on the preliminary estimation of β. If $\widehat{\beta}$ is the OLS estimator of β in Eq. (7), then underH_0 we have that:

$$\sup_\tau\left|\hat{V}_n(\tau)\right| \Rightarrow \sup_\tau\left|\frac{1}{f_\varepsilon\left(F_\varepsilon^{-1}(\tau)\right)}\left[\int_0^1 \underline{B}_{\Delta x}\underline{B}_\psi^T\right]^{-1}\int_0^1 \underline{B}_{\Delta x} d\left(B_\Psi^* - f_\varepsilon\left(F_\varepsilon^{-1}(\tau)\right)\right)B_\varepsilon^*\right|, \quad (14)$$

where $B_\varepsilon{}^*(\cdot)$ is the limit of the partial sum of ε_t. Thus, we may test varying-coefficient behavior based on the Kolmogoroff–Smirnoff statistic $sup_\tau\left|\hat{V}_n(\tau)\right|$. In generating critical values for the statistic $sup_\tau\left|\hat{V}_n(\tau)\right|$, Xiao uses re-sampling methods.[12]

Xiao (2009) mentions this method contributes in the following ways. First, it captures systematic influences of conditioning variables on the location, scale, and shape of the conditional distribution of the response. Second, it allows for additional volatility of the dependent variables in addition to the regressors and provides an interesting class of the cointegration model with conditional heteroskedasticity. Third, the estimated cointegrating coefficients may be influenced by the innovations received in each period and thus may alter over the innovation quantile. Finally, formal tests for the varying-coefficient cointegration relationship between variables are conducted by employing bootstrap-based tests.

[12] In our empirical works, we test the statistical significance by using the bootstrapped method 3000 times.

4.3. Non-linear granger-causality tests

In the following we introduce the non-parametric non-linear causality test developed by Diks and Panchenko (2006). Given strictly stationary time series processes $\{X_t\}\&\{Y_t\}$, where t is an integer, we say $\{X_t\}$ is a Granger cause of $\{Y_t\}$ if, for some $k\geq 1$, $(Y_{t+1},\ldots,Y_{t+k})|(F_{X,t},F_{Y,t})$ is not equivalent to $(Y_{t+1},\ldots,Y_{t+k})|(F_{Y,t})$, where $F_{X,t}$ and $F_{Y,t}$ are the respective information sets of X and Y at time t. In testing for Granger non-causality, the aim is to detect evidence against the null hypothesis:

$$H_0: \{X_t\} \text{ does not Granger cause } \{Y_t\}. \quad (15)$$

In practice, conditional independence is tested using finite lags l_X and l_Y:

$$Y_{t+1}|\left(\left(X_t^{l_X}; Y_t^{l_Y}\right) \text{is equivalent to } Y_{t+1}|Y_t^{l_Y}, \quad (16)$$

where $X_t^{l_X}=(X_{t-l_X+1},\ldots,X_t)$ and $Y_t^{l_Y}=(Y_{t-l_Y+1},\ldots,Y_t)$. We set $W_t=(X_t^{l_X},Y_t^{l_Y},Z_t)$, where $Z_t=Y_{t+1}$, as a vector with an invariant distribution and (l_X+l_Y+1)-dimension. It should be noted that Diks and Panchenko just consider the case for $l_X=l_Y=1$ and W is assumed to be a continuous random variable. Particularly, the joint probability density function $f_{X,Y,Z}(x,y,z)$ and its margins have to satisfy that:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)}\cdot\frac{f_{Y,Z}(y,z)}{f_Y(y)}. \quad (17)$$

By Eq. (17), the null hypothesis in Eq. (15) implies that:

$$q = E\left[f_{X,Y,Z}(X,Y,Z)f_Y(y) - f_{X,Y}(X,Y)f_{Y,Z}(Y,Z) = 0\right]. \quad (18)$$

Assume $\hat{f}_W(W_i)$ to be a local density estimator of a d_W-variate random vector W at W_i, where $\hat{f}_W(W_i) = (2\varepsilon_n)^{-d_W}(n-1)^{-1}\sum_{j,j\neq i} I_{ij}^W$ and $I_{ij}^W=I(\|W_i-W_j\|<\varepsilon_n)$ with the indicator function $I(\cdot)$ and the bandwidth ε_n, depending on the sample size n. Hence, we have the test statistic:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)}\cdot\sum_i\left(\hat{f}_{X,Z,Y}(X_i,Z_i,Y_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)\right. \quad (19)$$

Under the conditions of $l_X=l_Y=1$ and $\varepsilon_n=Cn^{-\beta}(C>0, \beta\in(1/4,1/3))$, C is a constant, and Diks and Panchenko (2006) show that:

$$\sqrt{n}\frac{(T_n(\varepsilon_n)-q}{S_n} \xrightarrow{D} N(0,1), \quad (20)$$

where D means convergence in distribution and S_n is an estimator of the asymptotic variance of $T_n(\cdot)$. In applications, we follow the suggestion of Diks and Panchenko (2006) to truncate the bandwidth by taking $\varepsilon_n=\max(Cn^{-2/7},1.5)$. In our empirical works, each ε_n for different futures oil price contracts is 1.5.

Table 2
Results of unit-root test.

Variable	ADF-test Level	ADF-test 1st diff.	PP-test Level	PP-test 1st diff.	KPSS-test Level	KPSS-test 1st diff.
Spot price	−1.24	−37.46**	−1.40	−77.60**	6.66**	0.08
Futures price of contract 1	−1.17	−37.15**	−1.35	−77.87**	6.67**	0.09
Futures price of contract 2	−1.15	−76.50**	−1.12	−76.51**	6.76**	0.10
Futures price of contract 3	−0.99	−76.46**	−0.97	−76.46**	6.81**	0.11
Futures price of contract 4	−0.88	−77.66**	−0.85	−77.67**	6.85**	0.12

Notes: The spot and futures prices are taken in natural logarithm. (**) denotes rejection at the 1% level or better. The null hypotheses are variable and have unit root in the ADF and PP tests, but the null hypothesis in the KPSS test is a variable without a unit root, respectively.

Table 3
Johansen cointegration test statistics.

	Maximum eigenvalue statistics	Trace eigenvalue statistics
Spot price vs. Futures price of contract 1		
H_0: $r=0$	132.67**	234.96**
H_0: $r\leq 1$	2.30	2.30
Spot price vs. Futures price of contract 2		
H_0: $r=0$	38.88**	40.17**
H_0: $r\leq 1$	1.29	1.29
Spot price vs. Futures price of contract 3		
H_0: $r=0$	34.94**	36.86**
H_0: $r\leq 1$	0.91	0.91
Spot price vs. Futures price of contract 4		
H_0: $r=0$	33.70**	34.32**
H_0: $r\leq 1$	0.62	0.62

Notes: The spot and futures prices are taken in natural logarithm. The lag length is chosen by AIC in Johansen's cointegration test. (**) denotes rejection at the 1% level or better.

5. Empirical analysis

As mentioned in the above section, we test unit roots of variables with ADF (1979), PP (1988), and KPSS (1992) tests. Table 2 shows that spot oil prices and futures oil prices for four contracts are integrated in order 1 ($I(1)$), respectively. We next use Johansen's linear cointegration method to examine whether the cointegration exists or not. The results of Tables 3–4 confirm the existence of cointegrating relationships between contemporaneous spot and various futures oil prices from both the eigenvalue and the trace test statistics. Table 4 displays the estimated long-run relationships and shows that all four types of oil futures contracts have long-run information content for the behavior of spot oil prices. This is the same as with the findings of Maslyuk and Smyth (2009b), in that spot and futures oil prices of the same grade as well as spot and futures prices of different grades are co-integrated. However, Maslyuk and Smyth (2009b) and Huang et al. (2009) neglect the stochastic cointegrating coefficients and the test of varying-coefficient behavior.

We further examine whether cointegrating coefficients are constant or not with Eq. (1). Table 5 shows the statistically significant existence of non-linear cointegrating relationships between contemporaneous spot and various futures oil prices.[13] The finite sample critical values are computed by means of Monte Carlo simulations using 3000 replications. This result also at least implies a possible bias in estimation and prediction. To sum up, the existence of time-varying cointegrating relationships is confirmed between spot and future oil prices, and therefore the next step is to discover such varying cointegrating coefficients. We further examine effects of quantile cointegrating relations. Table 6 and Fig. 1 show these cointegrating coefficients and their corresponding tracks across various quantiles. Table 6 presents that all estimated coefficients are statistically significant at the 1% level. More clearly, Fig. 1 offers a significant difference between low and high quantiles, except for the case of futures oil prices maturing in 2 months. In particular, the path for the case of 1-month futures contracts is different from the others. Significantly, the length of futures contracts influences their cointegrated relationships with spot prices.

[13] In our test, the residuals are stationary and not auto-correlative.

Table 4
Normalized cointegration vectors in Johansen's cointegration test.

Model	Spot price	Futures price
Contract 1 of futures prices	1	−0.998 (−0.001)
Contract 2 of futures prices	1	−0.984 (−0.007)
Contract 3 of futures prices	1	−0.973 (−0.012)
Contract 4 of futures prices	1	−0.964 (−0.016)

Notes: The spot and futures prices are taken in natural logarithm. The values in parentheses are standard errors.

Table 5
The test of quantile cointegration for the cointegrating relation.

Model	Sup $\lvert V(\tau)\rvert$	CV10	CV05	CV01
Spot price vs. Futures price of contract 1	54.624**	5.409	6.871	11.083
Spot price vs. Futures price of contract 2	22.580**	5.605	7.196	11.416
Spot price vs. Futures price of contract 3	28.879**	5.472	7.205	11.464
Spot price vs. Futures price of contract 4	41.818**	5.501	7.161	11.664

Notes: The frequency of the data is daily. CV10, CV05, and CV01 are the critical values of statistical significance at 10%, 5%, and 1%, respectively. (**) denotes rejection at the 1% level or better.

In the following, we analyze cointegrating relations individually shown in Figs. 2–5. For short 1-month contracts shown in Fig. 2, cointegrating coefficients are increasing with quantiles. Corresponding to the result of a conventional linear method, it implies that when spot oil prices are at a low level (low quantiles), the response of spot prices to futures prices is very small. However, when spot oil prices are at a high level (high quantiles), the responses become much bigger.

Through the explanation of the prospect theory, a high level of spot oil prices causes a steeper reflection based on the implicative reference point of losses versus the reference point of gains. Therefore, states of low spot prices reduce the sensitivity to shocks of futures oil prices, but in contrary states of high spot prices raise the sensitivity. However, when we examine the cases of long futures oil contracts, the results are different from 1-month futures oil contracts. The cointegrating coefficients of 1-month futures contracts are in a monotonic increasing trend, but the estimated cointegrating coefficients of long futures contracts do not vary much within quantiles 0.1 to 0.7. Except for the futures contracts in two months, they present a downward trend within high quantiles (0.7—0.9). Roughly speaking, the differential and smaller responses of spot oil prices to shocks of futures oil prices only happen when spot oil prices are at a high level. This difference should be ascribed to long contracts that provide much time for observation and waiting (i.e., options to wait). When spot oil prices are at a high level, people are less sensitive to shocks in futures oil prices of long maturities.

From the above results, we not only exhibit the effects of a reference point (here, it means the performance of spot oil prices), but

Table 6
The estimated coefficients of quantile cointegration.

	Low			Median			High		
Spot price and Futures price of contract 1									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Beta	0.993**	0.993**	0.995**	0.997**	1.000**	1.002**	1.004**	1.007**	1.008**
Spot price and Futures price of contract 2									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Beta	0.995**	0.994**	0.994**	0.994**	0.995**	0.995**	0.996**	0.996**	0.996**
Spot price and Futures price of contract 3									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Beta	0.992**	0.990**	0.990**	0.990**	0.989**	0.990**	0.991**	0.988**	0.984**
Spot price and Futures price of contract 4									
Quantile	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Beta	0.991**	0.987**	0.986**	0.985**	0.986**	0.988**	0.988**	0.984**	0.975**

Notes: (**) denotes rejection at the 1% level or better.

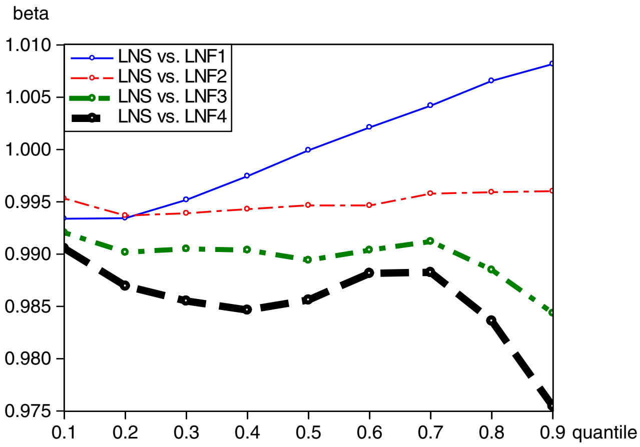

Fig. 1. Coefficients of quantile cointegration with spot and various futures prices.

also verify the long-run cointegrating relationship between spot and futures oil prices by using the quantile cointegration test. In the following, we further examine the effects of estimated error-correction terms (i.e., to examine the coefficient η in Eq. (2)); i.e., we consider the speed of adjustments to the long-run equilibrium. For convenient observation, we exhibit them in Fig. 6. There, we observe that in quantile cointegrating relationships between spot prices and futures oil prices of 1-month contracts (QC-SF1), the effects of linear error-correction term (EC) in low and high quantiles are lower than in median.

The performances of spot market states have a significant influence on the effect of EC. On the other hand, the results based on the contracts of futures oil prices of 2, 3, and 4 months have a similar trend.[14] These results differ from the results of 1-month futures contracts. The effects of EC are increasing with quantiles. In other words, lower (higher) spot price performances imply larger (less) effects of error-correction terms with respect to long futures contracts. These phenomena indicate that extreme oil market states usually distort their normal performances.

We now explore Granger-causalities between spot and various futures oil prices. Here, we also exercise linear (VECM) and non-linear methods (Diks and Panchenko, 2006). From Panel A in Table 7, we clearly see that bi-directional causalities exist between spot and various futures oil prices for linear and non-linear methods. Different to previous studies, we examine the causality across quantiles that include information from spot markets. In Panel B of Table 7, we see some differentials among various contracts and quantiles. First, we observe the examination of causalities running from futures prices to spot prices. From these statistic values, we find that futures oil prices significantly Granger-cause spot oil prices in the lowest quantile—0.1. When performances of spot markets are in the worst situation, shocks of futures prices can significantly cause an impact on spot prices, rather than in better situations.

Under the long futures contracts maturing in 2, 3, and 4 months, futures oil prices do not Granger-cause spot prices in high quantiles, except for the short 1-month contracts. Therefore, we deduce that when market participants have much time to observe (i.e., to make a decision based on longer futures contracts), they do not expect the effects of futures prices to work on spot prices, except when spot markets are showing lower performances. Furthermore, 1-month futures contracts are usually the most actively traded, which matches the consistent expectations traded. Obviously, market participants do not expect futures oil prices to show a precise prediction to future spot prices. This may be due to the effect of adaptive learning, as by that, the past several times of wrong prediction drive market participants to not believe the predictability of futures prices. An exception is when spot markets are in the worst situation, because they then expect futures prices to show a sign of reversing back.

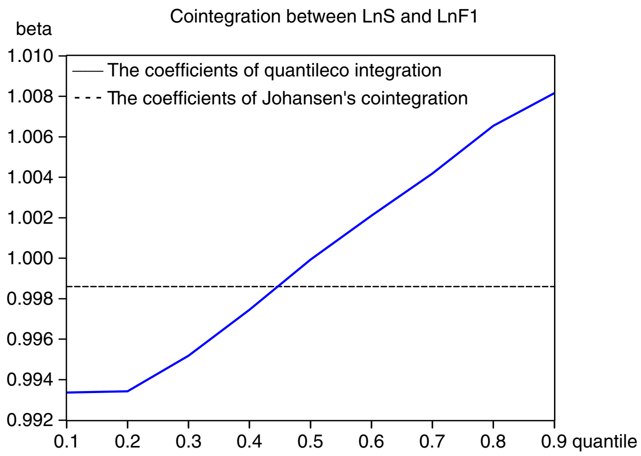

Fig. 2. Coefficients of quantile cointegration and Johansen's cointegration between spot prices and futures prices with 1-month maturity.

[14] In Fig. 6, we denote QC-SF2, QC-SF3, and QC-SF4 as the quantile cointegrating relationships between spot prices and futures oil prices of 2-, 3- and 4-month contracts, respectively.

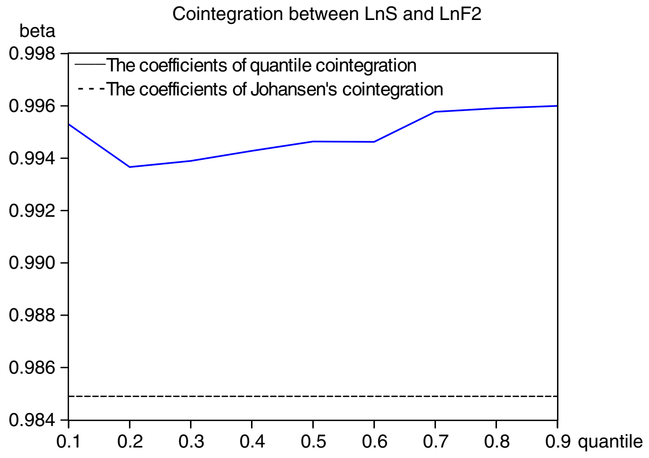

Fig. 3. Coefficients of quantile cointegration and Johansen's cointegration between spot prices and futures prices with 2-month maturity.

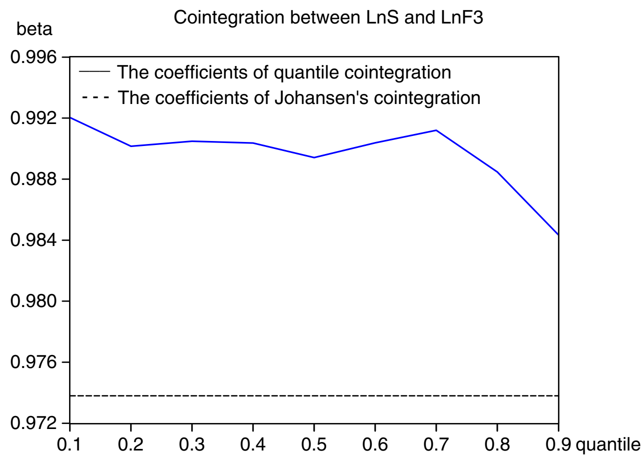

Fig. 4. Coefficients of quantile cointegration and Johansen's cointegration between spot prices and futures prices with 3-month maturity.

Different to previous studies in which spot oil prices Granger-cause futures prices conditional on every kind of futures contracts and various quantiles, people believe the performances of spot markets will directly influence futures markets. In particular, the statistical evidence is significant mostly within median and high quantiles (0.4–0.9). In other words, when spot markets perform better, the optimistic sentiment will drive people to expect better performances in the futures markets.

This paper finally tests market efficiency under two different hypotheses – the expectations hypothesis and the no arbitrage rule – derived by Brenner and Kroner (1995). To fit the hypotheses, we examine them with monthly data.[15] Similarly, we examine unit root tests and Johansen's cointegration tests for the relative variables and models. These results are shown in Tables 8–12. It is noticeable that even after considering monthly data, non-constant cointegration relationships between spot and futures oil prices still emerge. In the following, we examine market efficiency under different hypotheses.

We examine the efficiency of crude oil markets with Eq. (4) for the expectations hypothesis. First, we show the results of testing the effect of quantile cointegration in Table 13. It should be noted that if the effect of quantile cointegration does not exist, then we examine market efficiency with a linear estimation. When we set critical values at the 1% level, the effects of quantile cointegration exist between spot prices and futures oil prices maturing in 3 and 4 months, but not in contracts of 1 and 2 months. Table 14 presents the results of testing for efficiency based on the expectations hypothesis. Except for the 1-month futures contract, efficiency does not exist in the linkage of the spot oil price and the futures oil price of contracts maturing in 2, 3, and 4 months, respectively. Not surprisingly, futures oil prices of short maturities contain more completely available information than the futures prices of long maturities, but the cointegrating coefficients varying with innovations indeed exist in the long futures contracts maturing in 3 and 4 months. This should be related to the adjustments, on the impacts of futures prices of long maturities on spot prices, according to current performances of spot markets.

To test market efficiency under the no arbitrage rule, we examine first the effect of the quantile cointegration shown in Table 15, which presents no effect of quantile cointegration at the 1% level. Thus, we utilize the linear estimation to test the model in Eq. (5), and the empirical results are reported in Table 16. It shows that, except for futures contracts maturing in four months, market efficiency under the no arbitrage rule holds under the linkage of spot oil prices and futures oil prices for contracts maturing in 1, 2, and 3 months, respectively.

In testing market efficiency, one may consider the influence of exogenous shocks. For example, the findings of Switzer and El-Khoury (2007) are consistent with the expectations hypothesis, even during episodes of extreme conditional volatility. Here, we examine market efficiency based on different innovations of spot markets, although such effects merely appear in 3- and 4-month futures contracts under the expectations hypothesis. Our empirical results are not consistent with the expectations hypothesis, even conditional on various spot market performances. Both the results of Switzer and El-Khoury (2007) and ours seem to represent that exogenous shocks do not influence the market efficiency for spot–futures oil prices under the expectations hypothesis.

Generally speaking, if futures prices reflect all of the relative available information, then the spot price should be consistent with respect to prior futures prices. In the above examination, we find that the results of testing the efficient market hypotheses are relative with the length of the futures contracts. It should be reasonable that the length of the futures contracts may be too long to reflect all available information. Therefore, the efficient market hypotheses seem to afford a shorter length of futures contracts.

From the above analysis, in addition to verifying the existence of non-linear long-run relationships, we also explore the effects of advantageous and disadvantageous reference points (spot oil

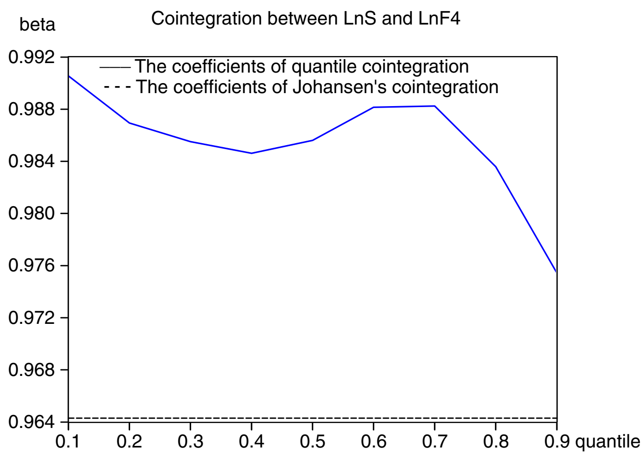

Fig. 5. Coefficients of quantile cointegration and Johansen's cointegration between spot prices and futures prices with 4-month maturity.

[15] Here, the current terms – spot price and risk-free returns – are adopted on the 25th business day or prior to the 25th calendar day of the month, and the lagged-term futures prices are adopted on the first business day after the 25th calendar day of the month.

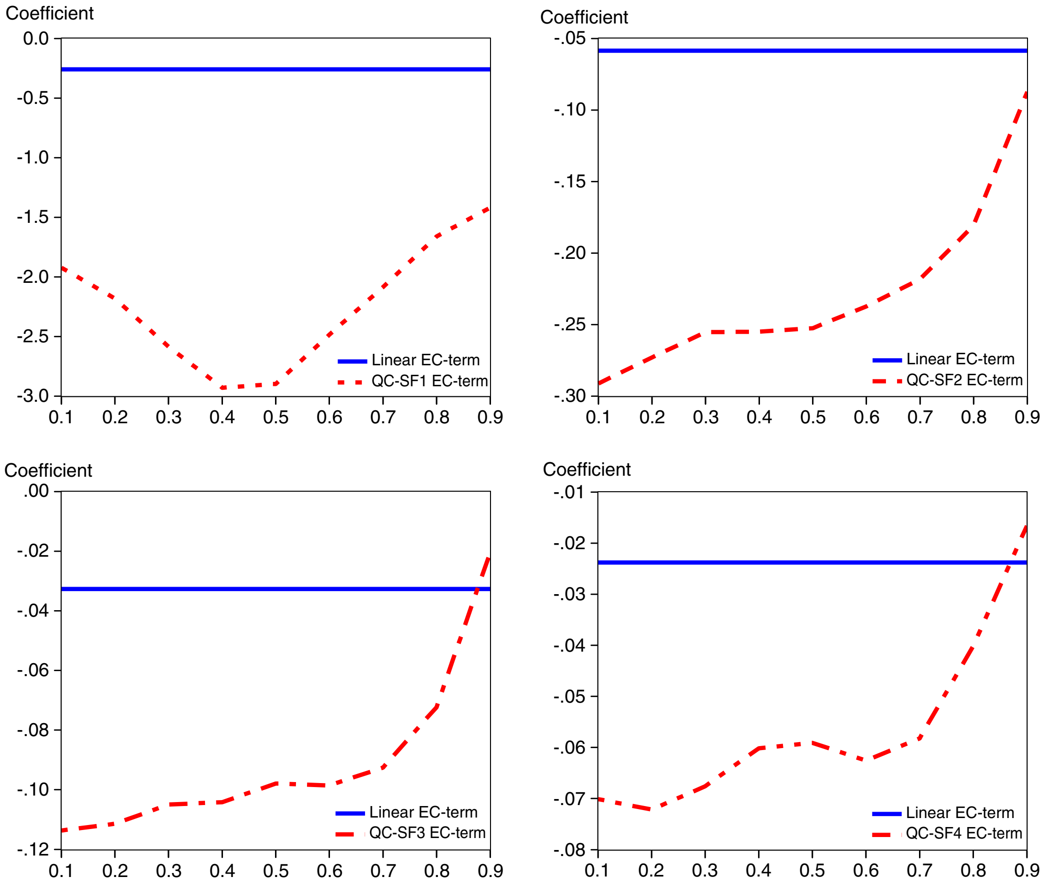

Fig. 6. The estimated coefficients of error-correction terms extracted from linear and quantile cointegrating models.

markets) that cause different effects on cointegrating relationships and causalities, respectively. Not surprisingly, this phenomenon is found in economic and financial areas. It is worth noting that although some theoretic models have described spot–futures price correlations, there is still much deviation when comparing with real decisions, especially for markets in extreme states. Like the appearance in this

Table 7
The non-Granger-causality (non-GC) test (pair-wise).

Panel A.

	Linear non-GC test	Non-linear non-GC test
Null hypothesis	VEC (Chi-sq.)	Diks and Panchenko (2006) (T-statistic)
F1 →× S	199.7**	9.2**
F2 →× S	248.8**	8.7**
F3 →× S	250.2**	8.5**
F4 →× S	245.7**	8.3**
S →× F1	734.9**	13.9**
S →× F2	335.2**	14.0**
S →× F3	238.1**	13.6**
S →× F4	227.9**	13.2**

Panel B.

	Quantile non-GC test (F-statistic)								
Null hyp.	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
F1 →× S	17.3**	5.1**	3.3**	2.2**	2.1**	2.4**	2.8**	4.0**	5.2**
F2 →× S	7.5**	2.7**	2.7**	2.7**	1.5	1.2	1.9	2.3*	1.6
F3 →× S	4.4**	1.7	1.7	2.0*	0.9	0.8	1.4	2.1*	1.5
F4 →× S	3.8**	1.7	1.5	1.7	0.6	0.5	1.3	1.6	1.2
S →× F1	60.7**	87.3**	288.4**	333.7**	441.3**	436.5**	139.2**	75.1**	56.0**
S →× F2	94.1**	99.7**	143.9**	179.5**	186.7**	222.0**	186.7**	203.3**	145.6**
S →× F3	95.6**	98.2**	156.6**	160.0**	171.0**	122.8**	102.7**	111.0**	166.4**
S →× F4	76.6**	97.3**	120.5**	116.6**	112.8**	173.5**	90.8**	119.2**	158.1**

Notes: Variables S, F1, F2, F3, and F4 mean the first difference of spot price, futures prices of contracts of 1-, 2-, 3-, and 4-months taken in natural logarithm, respectively. The null hypothesis: X →× Y means that X does not cause Y. (*) and (**) denote rejection at the 5% and 1% levels or better, respectively. Here, the number of lags (according to SIC) for pairs (S, F1), (S, F2), (S, F3), and (S, F4) in the VECM and quantile models is 21, 9, 9, and 8, respectively, but the lag length in the non-linear method is one for every kind of futures contracts. In particular, the constant term we estimate in the non-linear method is within the range from 7 to 9.

Table 8
Results of unit-root test: monthly data.

	ADF-test		PP-test		KPSS-test	
Variable	Level	1st diff.	Level	1st diff.	Level	1st diff.
Spot price	−1.46	−17.19**	−1.24	−17.46**	1.40**	0.05
Futures price of contract 1	−1.26	−16.04**	−1.16	−16.34**	1.39**	0.08
Futures price of contract 2	−1.11	−15.75**	−1.05	−15.90**	1.40**	0.09
Futures price of contract 3	−0.99	−15.67**	−0.98	−15.76**	1.40**	0.10
Futures price of contract 4	−0.88	−15.56**	−0.94	−15.60**	1.40**	0.10
Risk-free rate	−1.33	−6.62**	−1.48	−16.36**	1.03**	0.05

Notes: The spot and futures prices are taken in natural logarithm. (**) denotes rejection at the 1% level or better. The null hypotheses of variables are with unit roots in the ADF and PP tests, but the null hypothesis of variables is stationary in the KPSS test, respectively.

Table 9
Johansen's cointegration test statistics under the expectations hypothesis.

	Maximum eigenvalue statistics	Trace eigenvalue statistics
Spot price vs. Futures price of contract 1		
H_0: $r=0$	26.61**	27.65**
H_0: $r\leq 1$	1.04	1.04
Spot price vs. Futures price of contract 2		
H_0: $r=0$	28.10**	29.18**
H_0: $r\leq 1$	1.07	1.07
Spot price vs. Futures price of contract 3		
H_0: $r=0$	20.37**	20.41**
H_0: $r\leq 1$	0.04	0.04
Spot price vs. Futures price of contract 4		
H_0: $r=0$	36.17**	37.43**
H_0: $r\leq 1$	1.25	1.25

Notes: The spot and futures prices are taken in natural logarithm. The lag length is chosen by AIC in Johansen's cointegration test. (**) denotes rejection at the 1% level or better.

paper, market innovations have non-neglectable influences on long-run relations and causalities for the linkage of spot and futures oil prices.

6. Conclusions

This paper employs novel quantile cointegrating regressions of Xiao (2009) to examine cointegration, causalities, and market efficiency for the linkage of spot and futures oil markets. In contrast to a traditional linear estimation conditional on mean distributions of dependent variables, this method allows us to explore cointegration relationships conditional on quantiles in the distributions of spot oil prices. In our results, the effect of quantile cointegration indeed exists

Table 10
Normalized cointegration vectors in Johansen's cointegration test under the expectations hypothesis.

Model	Spot price	Futures price
Contract 1 of futures prices	1	−0.996
		(−0.005)
Contract 2 of futures prices	1	−0.983
		(−0.009)
Contract 3 of futures prices	1	−0.970
		(−0.013)
Contract 4 of futures prices	1	−0.968
		(−0.015)

Notes: The spot and futures prices are taken in natural logarithm. The values in parentheses are standard errors.

Table 11
Johansen's cointegration test statistics under the no arbitrage rule.

	Maximum eigenvalue statistics	Trace eigenvalue statistics
Spot price vs. Futures price of contract 1		
H_0: $r=0$	25.82**	36.93**
H_0: $r\leq 1$	10.80	11.11
H_0: $r\leq 2$	0.30	0.31
Spot price vs. Futures price of contract 2		
H_0: $r=0$	27.95**	37.79**
H_0: $r\leq 1$	9.56	9.85
H_0: $r\leq 2$	0.29	0.29
Spot price vs. Futures price of contract 3		
H_0: $r=0$	28.06**	38.24**
H_0: $r\leq 1$	9.96	10.18
H_0: $r\leq 2$	0.22	0.22
Spot price vs. Futures price of contract 4		
H_0: $r=0$	25.27**	34.99**
H_0: $r\leq 1$	8.59	9.71
H_0: $r\leq 2$	1.12	1.12

Notes: The spot and futures prices are taken in natural logarithm. The lag length is chosen by AIC in Johansen's cointegration test. (**) denotes rejection at the 1% level or better.

Table 12
Normalized cointegration vectors in Johansen's cointegration test under the no arbitrage rule.

Model	Spot price	Futures price	Risk-free rate
Contract 1 of futures prices	1	−0.997	−0.124
		(−0.006)	(−1.910)
Contract 2 of futures prices	1	−0.978	0.847
		(−0.010)	(−1.722)
Contract 3 of futures prices	1	−0.961	0.905
		(−0.015)	(−1.639)
Contract 4 of futures prices	1	−0.927	3.0424
		(−0.019)	(−1.513)

Notes: The spot and futures prices are taken in natural logarithm. The values in parentheses are standard errors.

Table 13
The test of quantile cointegration. Description: The test is for the market efficiency under expectations hypothesis with the model: $LnS_t = \alpha + \beta LnF_{t-M} + \sum_{i=-K}^{K} \omega_i \Delta LnF_{t-i} + \varepsilon_t, M = 1, 2, 3, 4$.

Model	Sup $\lvert V(\tau)\rvert$	CV10	CV05	CV01
Spot price vs. Futures price of contract 1	5.03	5.11	6.08	8.08
Spot price vs. Futures price of contract 2	8.52*	5.49	6.49	8.86
Spot price vs. Futures price of contract 3	10.89**	5.43	6.56	10.45
Spot price vs. Futures price of contract 4	17.95**	5.45	6.74	10.67

Notes: The frequency of the data is monthly. CV10, CV05, and CV01 are the critical values of statistical significance at 10%, 5%, and 1%, respectively. (*) and (**) denote rejection at the 5% and 1% levels or better, respectively.

Table 14
The test of market efficiency under the expectations hypothesis.

Model	Method	Result
Spot price vs. Futures price of contract 1	Linear cointegration	The market is efficient (p-value is 0.82)
Spot price vs. Futures price of contract 2	Linear cointegration	The market is not efficient (p-value is 0.02)
Spot price vs. Futures price of contract 3	Quantile cointegration	The market is not efficient for each quantile (p-value is approximate to 0 for each quantile)
Spot price vs. Futures price of contract 4	Quantile cointegration	The market is not efficient for each quantile (p-value is approximate to 0 for each quantile)

Note: The null hypothesis is that ($\alpha=0,\beta=1$) with the Wald test.

Table 15
The test of quantile cointegration. Description: The test is for the market efficiency under the no arbitrage profit rule with the model: $LnS_t = \alpha + \beta_1 LnF_{t-M} + \beta_2 R_t + \sum_{i=-K}^{K} \omega_i \Delta LnF_{t-i} + \sum_{j=-L}^{L} \psi_j \Delta R_{t-j} + \varepsilon_t, M = 1, 2, 3, 4.$

Model	Sup $\vert V(\tau)\vert$	CV10	CV05	CV01
Spot price vs. Futures price of contract 1	2.45	12.93	16.43	24.51
Spot price vs. Futures price of contract 2	6.03	12.14	15.39	23.80
Spot price vs. Futures price of contract 3	10.52	10.84	13.40	20.19
Spot price vs. Futures price of contract 4	18.33*	10.31	12.82	18.68

Notes: The frequency of the data is monthly. CV10, CV05, and CV01 are the critical values of statistical significance at 10%, 5%, and 1%, respectively. (*) denotes rejection at the 5% level.

in the linkage between spot and futures oil prices. This condition could drive a linear estimation for cointegration to produce an imprecise prediction. We find that the length of futures contracts, not surprisingly, has an influence on cointegrating relationships between spot and futures oil prices. These results inevitably relate to long futures contracts that provide much time to wait and observe, rather than for an immediate decision so as on short-term futures contracts.

In testing Granger-causalities, we also show that spot and futures oil prices are influenced by quantiles and futures contracts. Our findings differ from linear (VECM) and non-linear methods, which present bi-directional causalities. In our results, spot oil prices indeed cause futures oil prices. However, except for 1-month futures contracts, the causality running from futures oil prices to spot prices merely exists only in lower quantiles. Market participants pay significantly more attention to spot oil markets rather than futures oil markets. Hence, in most of our results, spot oil prices Granger-cause futures oil prices. In testing market efficiency, we find that short futures contracts seem to be consistent with efficient market hypotheses, although the effect of quantile cointegration does not work out in some cases. The no arbitrage rule is also more practical than the expectations hypothesis in hedging risk.

Comparing with recent findings of asymmetric performances among different market states (booming and depressing markets) and in addition to asymmetric effects of oil prices shocks, such asymmetric effects are less considered in energy markets, especially for the confirmed cointegrating relationship between spot and futures oil prices. Thus, we hope our empirical results are able to offer wide and different aspects to investors and firms for investing and hedging, respectively. We provide a more accurate model to understand the non-linear relationship, thus enabling a better forecast of the future dynamics of the oil or financial market. Policy-makers should take the non-linear behavior of the spot–future oil prices nexus into account when building the estimation and prediction modes for energy or financial markets. Finally, if the firms want to hedge risk by futures contracts, then they should choose the length of futures contracts appropriately to avoid an imprecise prediction.

Table 16
The test of market efficiency under the no arbitrage rule.

Model	Method	Result
Spot price vs. Futures price of contract 1	Linear cointegration	The market is efficient (p-value is 0.91)
Spot price vs. Futures price of contract 2	Linear cointegration	The market is efficient (p-value is 0.32)
Spot price vs. Futures price of contract 3	Linear cointegration	The market is efficient (p-values is 0.12)
Spot price vs. Futures price of contract 4	Linear cointegration	The market is not efficient (p-values is 0.04)

Notes: The null hypothesis is that ($\beta_1 = 1, \beta_2 = 1$). We examine with the Wald test rejecting in the 5% level.

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