

# Hedge Ratio Variation Under Different Energy Market Conditions: New Evidence by Using Quantile–Quantile Approach



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**Abstract** In this research, we investigated the long-run and causal relationships between spot and futures prices of crude oil, natural gas, and gasoline using monthly data and considering the variables' distribution. The quantile co-integration and quantile causality tests provided strong evidence for the long-run and causal relationships among the variables. Furthermore, we examined the optimal hedge ratio (OHR) at different quantiles of the series using the recently developed quantile on the quantile approach. For all three commodities, our results confirmed the asymmetric response of the spot market to the futures market. Furthermore, our findings show that in a bullish market and for a large positive shock, the value of OHR is significantly greater than one. We observed lower fluctuations in the OHR as the maturities of the futures contracts increased. We discuss the policy implications of our research in detail in the Conclusion section.

**Keywords** Hedge ratio · Energy market · Quantile-on-quantile (QQ) approach · Causality · Futures market

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## Introduction

Price movements in the energy market are crucial because energy plays a vital role in the world's economies and human life. The high volatility in energy prices since the 1990s is due to several historical developments, including the deregulation of energy markets, the Asian financial crisis in 1997, and the 2008 global financial crisis (Lien et al., 2016; Lang & Auer, 2019) have increased the need for an appropriate protection strategy. Hedging by using futures contracts makes the problem of "finding an appropriate hedge ratio" vital. In calculating the optimal hedge ratio (OHR), estimations are mostly based on the average (expected) relationship between spot and futures prices. This approach ignores the tail distribution of the variables (Lien et al., 2016; Shrestha et al., 2018). However, the widely documented non-normal distribution of financial variables makes considering the quantiles of the variables essential. To fill this gap, we used the recently developed quantile-on-quantile (Q-Q) (Sim & Zhou, 2015) approach to estimate the minimum-variance (MV) hedge ratio for crude oil, natural gas, and gasoline markets. Besides, to have a better understanding of the relationship between these variables, we examined long-run and causal relationships by using methods that consider the distribution of the variables.

Crude oil, natural gas, and gasoline are the major energy market commodities. Crude oil is one of the most strategic resources which has substantial effects on many macroeconomic variables, including economic growth (Cheng et al., 2019; Gupta & Banerjee, 2019; Wang et al., 2019; Wang & Wang, 2019), currency fluctuations, and inflation (Lang & Auer, 2019). Due to its high energy density and relatively more convenient transportation, it has been the primary energy source for many industries. The energy used for transportation has been satisfied in large with petroleum products. Besides, it is a raw material for many other products (Wang & Wang, 2019). Although crude oil remains the most critical energy source, the ever-increasing concerns about environmental degradation have enhanced natural gas's importance as a cleaner alternative (Li et al., 2019; Lin et al., 2019). The US has used thirty trillion cubic feet (TCF) of natural gas in 2018, which equals 31% of total US primary energy consumption. It is an important energy source for electric power generation, industry, residential use, and transportation (Energy Information Administration [EIA], 2019a, b). Gasoline is the most consumed petroleum product in the US, with 392 million gallons per day, equal to about 45% of total US petroleum consumption (EIA, 2019a, b).

The significant role of these energy commodities makes their price fluctuations quite essential. Many factors, such as natural disasters, extraction costs, inventory costs, exchange rates, geopolitical instability, climate change, and military conflicts, can cause significant volatility in energy prices. Energy price fluctuations can have substantial impacts on the global economy, and even they may lead to economic and political instability (Wu & Zhang, 2014; Zhang et al., 2015; Billio et al., 2018; Lang & Auer, 2019). Hence, it is essential to hedge in the energy market (Shrestha et al., 2018; Halkos & Tsirivis, 2019).

Futures contracts are among the most important financial instruments, with 17.15 billion trades globally in 2018. A notable feature of the futures market is that it is where price discovery takes place. Futures contracts are widely used to hedge against energy price volatility because of their useful characteristics such as low transaction costs, high liquidity, low counterparty risk, and low margin requirements. Determining the optimal number of futures positions to be held to reduce the risk associated with spot price fluctuations is one of the most critical challenges in hedging and has been widely discussed in the theoretical and empirical literature.

There is a complex linkage between spot and futures prices. The spot market may react asymmetrically to the changes in the futures market. For instance, futures price shocks may have different effects on the spot market, depending on whether the spot market is bearish or bullish. Besides, the impact of a large futures price shock on the spot market may differ from that of a smaller shock. Also, spot prices may respond asymmetrically to adverse versus positive futures price shocks. The effect of futures price shocks on the spot market may vary depending on the market conditions, the nature, and the magnitude of the shocks; thus, it is heterogeneous. These asymmetric impacts may cause diverse co-movement behaviors or conditional covariance among spot and futures prices (Meneu & Torro, 2003; Chang et al., 2010b). Therefore, while investigating the spot-futures market relationship to consider the potential non-linear characteristics is a necessity. The complicated relationship between the spot and futures market also affects the OHR as well. This implies that the OHR may vary depending on the factors mentioned above. Hence, conventional frameworks, like OLS, are not suitable to determine the OHR. Although comparatively more recent approaches have some desirable characteristics than OLS, they cannot capture the overall dependence structure.

In this study, we investigated the relationship between spot and futures prices for three major energy commodities. Our research contributes to the literature in several ways. While exploring the cointegration and causal relationship, literature mostly ignores the distribution of the variables and focuses on the average relationship. We employed quantile cointegration (Xiao, 2009) and quantile Granger causality tests to have a better understanding of the relationship between the energy market spot and futures prices by considering the distribution of these variables. In the OHR investigation, choices of the appropriate objective function and methodology are vital. Regarding the first issue, following Lien et al. (2016) and Shrestha et al. (2018), we employed the MV hedge ratio. Regarding the second issue, considering the previous literature's deficiencies, we engaged the recently developed QQ approach (Sim & Zhou, 2015) to uncover state-dependent OHR variations under different market conditions. The OHR has many advantages over the other methods employed in the literature. This model is an amalgam of quantile regression and nonparametric estimation techniques and enables us to regress each quantile of spot returns against the entire distribution of futures returns (Gupta et al., 2018; Han et al., 2019; Mallick et al., 2019; Mo et al., 2019; Shahzad et al., 2019). Hence, it can capture a non-linear relationship and provides dynamic OHR throughout the entire distribution of spot and futures prices. The QQ approach enables us to provide a more inclusive measure of the relationship between spot and futures prices

for three major energy commodities considering the performance of the markets and the sign and size of these shocks. These findings can be used to establish more efficient hedging strategies. We also examined the effect of time on the maturity of the futures contract on the OHR, which provides valuable information for portfolio managers.

The rest of the study includes the literature review, data, methodology, empirical findings, and conclusion.

## Literature Review

Discovering the OHR for futures contracts has been one of the most discussed areas in the finance literature. Regarding the discovery of the OHR, two strands of studies have been mainly considered in the literature. The first group of studies aims to discover the OHR based on different objective functions. Reducing the volatility of the hedged portfolio; increasing the expected utility of the hedged portfolio, minimizing the mean extended-Gini (MEG), minimizing the generalized semivariance (GSV), and minimizing the Value-at-Risk (VaR) are examples of different objective functions that have been discussed in exploring the OHR (Shalit, 1995; De Jong et al., 1997; Lien & Tse, 2000; Hung et al., 2006). The performance of each of these objective functions has been tested extensively.

Among several objective functions, the most popular one has been the MV hedge ratio. Many researchers documented the desirable characteristics of the MV hedge ratio (Johnson, 1960; Ederington & Salas, 2008). This approach is based on minimizing the variance of the hedged portfolio and is quite simple to understand and estimate. To derive the MV hedge ratio, the underlying commodity spot returns are regressed on futures returns, where the slope coefficient represents the MV hedge ratio (Ederington, 1979). MV is the most widely used hedging strategy in the literature (Hung et al., 2011; Cotter & Hanly, 2015; Turner & Lim, 2015; Wang et al., 2015; Markopoulou et al., 2016; Park & Shi, 2017; Chun et al., 2019; Wang et al., 2019). Due to its desirable properties and wide use in the literature, we used the MV hedge ratio as our objective function.

The second group of studies aims to discover the OHR by using different models. Early literature claimed that the slope coefficient in OLS regression is the OHR (Johnson, 1960; Stein, 1961; Ederington, 1979). Although the conventional ordinary least squares (OLS) has been the most widely used method, it ignores several problems such as long-term relationship (cointegration), conditional heteroscedasticity, and the time-varying structure of the hedge portfolio. Due to the OLS method's insufficiency, later, to solve the specified problems, many other econometric methods have been employed in the estimation of OHR. The methods that have been used to discover the hedge ratio includes constant conditional correlation (CCC), dynamic conditional correlation (DCC) (Lanza et al., 2006), diagonal BEKK (Chang et al., 2010b), bivariate error correction framework with a GARCH error structure (Kroner & Sultan, 1993), VARMA-GARCH, VARMA asymmetric

(Manera et al., 2006), regime-switching GARCH (Hung et al., 2011), and Bayesian multi-chain Markov switching GARCH (Billio et al., 2018). These studies have contradictory claims on the performance of the econometric methods employed. For example, Chang et al. (2010b) stated that the CCC-GARCH model is superior to the other multivariate GARCH frameworks; however, Chang et al. (2011) found that the performance of multivariate GARCH models is better in exploring the OHR.

In the conventional regression framework, the central focus is on the nexus between spot market returns and futures market returns on average to get the OHR, which leaves us with no information about the changes in hedge ratio at various quantiles of the distributions of the two variables (Shrestha et al., 2018). Although, until recently, many different methods were used to estimate the OHR, none of them targets the mentioned fundamental problem and is not flexible enough to provide a complete picture of the relationship among the variables under investigation. Chang et al. (2010b) found that the OHR might be different for different market states, which calls for taking different market states into account while analyzing the OHR. Lien et al. (2016) proposed a linear conditional quantile model that estimates different hedge ratios for different quantiles of spot returns, which is named the quantile hedge ratio. They found that OHR depends on various quantiles like upper and lower tails of spot returns distribution.

Many studies have investigated the OHR for energy market commodities. Some researchers argued that the OHR between spot and futures prices might depend on several factors such as the holding period of the hedger, maturity of the futures contract, and price discovery level. Chen et al. (1987) analyzed the differences in hedging effectiveness with different holding periods and maturities. They found that the longer hedger's horizon and nearer futures contract maturity lead to a more effective hedging strategy for crude oil, leaded gasoline, and heating oil. Conlon and Cotter (2013) demonstrated that as the hedging horizon increases, hedging effectiveness increases in the heating oil market. They also revealed that hedging effectiveness is not sensitive to different objective functions. However, until recently, researchers did not consider the effect of the market state on the OHR.

Several studies related to the energy market have recently utilized quantile regression (Reboredo & Ugolini, 2016; Zhu et al., 2016; Khalifa et al., 2017). In their recent research, Shrestha et al. (2018) applied the method of Lien et al. (2016) to the energy market. They found that the quantile hedge ratio has an inverted U-shape for crude oil and heating oil. Besides, they discovered that OHR could vary according to the level of price discovery in the futures market. Their findings confirmed the idea that the hedge ratio strongly depends on the different spot market states for crude oil, heating oil, and natural gas. However, there is still one area of study that is neglected, in which the effects of various futures market conditions on the OHR have not been explored in the hedge ratio literature annals. In this study, we extended the literature on the exploration of hedge ratios with the use of a new method proposed by Sim and Zhou (2015), referred to as the QQ approach, which allows us to investigate in detail the variation of hedge ratio in different quantiles of spot and future returns simultaneously.

## Data

We used monthly data covering the periods February 1986 to March 2019 for crude oil, February 1997 to March 2019 for natural gas, and January 2006 to March 2019 for gasoline. Cushing, OK crude oil 1, 2, 3, and 4 months' future contracts (Dollars per Barrel), Natural Gas 1, 2, 3, and 4 months' futures contracts (Dollars per Million Btu) and New York Harbor Reformulated RBOB Gasoline 1, 2, 3, and 4 months' future contracts (Dollars per Gallon) were used as proxies for oil, natural gas, and gasoline futures prices, respectively. For spot prices of these commodities, we used Cushing, OK WTI Spot Price FOB (Dollars per Barrel), Henry Hub Natural Gas Spot Price (Dollars per Million Btu), and Los Angeles Reformulated RBOB Regular Gasoline Spot Price (Dollars per Gallon) as proxies. We collected data from Independent Statistics & Analysis US Energy Information Administration database and converted them into logarithmic form.

We report the descriptive statistics of the variables in Table 1. Skewness and kurtosis are far from 0 and 3, respectively, which indicate the skewed distribution and fat tails. These are typical characteristics of much financial time series. A notable finding in Table 1 is the results of the Jarque-Bera (Jarque and Bera, 1980) test, which reveals the non-normality of all of the variables. These findings indicate the benefit of using the QQ method to investigate the relationship between spot and futures prices.

To investigate the stochastic properties of our variables, we applied the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) unit root test. To confirm our findings, we also employed Zivot and Andrews (ZA) (Zivot & Andrews, 1992)

**Table 1** Descriptive statistics

Variables	Mean	Minimum	Maximum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
OIL	0.002	-0.394	0.392	0.087	-0.449	5.622	127.414	0.000
Futures-1	0.002	-0.396	0.377	0.087	-0.443	5.453	112.848	0.000
Futures-2	0.002	-0.353	0.320	0.081	-0.505	5.084	88.911	0.000
Futures-3	0.002	-0.326	0.283	0.077	-0.564	5.014	88.369	0.000
Futures-4	0.003	-0.307	0.263	0.073	-0.620	5.017	92.968	0.000
NGAS	-0.001	-0.473	0.478	0.134	-0.003	4.357	20.420	0.000
Futures-1	0.000	-0.396	0.406	0.121	0.030	3.752	6.305	0.043
Futures-2	0.000	-0.377	0.362	0.113	0.019	3.538	16.254	0.000
Futures-3	0.001	-0.372	0.296	0.104	0.020	3.473	22.496	0.000
Futures-4	0.001	-0.231	0.256	0.089	0.020	3.068	29.069	0.000
RBOB	0.001	-0.516	0.454	0.119	-0.295	6.301	74.489	0.000
Futures-1	0.001	-0.384	0.353	0.102	-0.554	5.126	38.082	0.000
Futures-2	0.001	-0.364	0.284	0.095	-0.798	5.001	43.420	0.000
Futures-3	0.001	-0.342	0.212	0.088	-0.842	4.885	42.305	0.000
Futures-4	0.000	-0.332	0.245	0.082	-0.803	5.081	45.770	0.000

Source: Author estimations

**Table 2** Results of unit root tests

Variables	ADF (level)	ADF ( $\Delta$ )	ZA (level)	Break period	ZA ( $\Delta$ )	Break period
OIL	-0.382	-6.483***	-1.283	2006 M02	-9.493***	2008 M08
Futures-1	-1.042	-9.723***	-1.958	2010 M10	-11.592***	2011 M01
Futures-2	-1.583	-6.402***	-2.495	2015 M03	-10.583***	2015 M03
Futures-3	0.258	-5.763***	-0.522	2010 M02	-7.448***	2010 M02
Futures-4	0.781	-7.535***	0.854	2012 M11	-10.421***	2012 M11
NGAS	0.876	-5.321***	-2.471	2009 M07	-12.581***	2005 M05
Futures-1	-1.294	-5.631***	-1.448	2004 M07	-8.664***	2011 M07
Futures-2	-0.993	-3.491***	-1.341	2013 M12	-9.315***	2017 M09
Futures-3	-0.251	-9.597***	-0.472	2007 M05	-6.942***	2019 M01
Futures-4	-1.335	-7.625***	-1.003	2005 M11	-8.593***	2016 M05
RBOB	-2.044	-4.592***	-2.045	2016 M10	-10.615***	2009 M07
Futures-1	-1.448	-3.842***	-1.753	2009 M03	-11.374***	2011 M04
Futures-2	-0.921	-6.414***	0.515	2013 M01	-9.329***	2018 M06
Futures-3	-0.337	-6.097***	0.994	2007 M08	-8.624***	2015 M10
Futures-4	1.475	-5.669***	-0.551	2017 M04	-9.553***	2008 M12

Note: The values in the table specify the test statistics of the ADF and ZA tests

The asterisk \*\*\*, \*\*, and \* represent the significance level at 1%, 5%, and 10%, respectively

unit root test, which incorporates one endogenous structural break. Table 2 illustrates the results of these unit root tests. Both ADF and ZA unit root tests indicate that the natural logarithm of oil, natural gas, and gasoline and four futures contracts returns series are not stationary at their levels, while the first difference forms of all these variables are stationary. This finding requires the investigation of the cointegrating relationship between the variables.

## Methodology

We further examined the long-run relationship among the variables using the quantile cointegration model developed by Xiao (2009). This model can capture the variation of quantile coefficients. To create the critical values, we used 1000 Monte Carlo simulations. We also used 19 equal quantiles from 0.05 to 0.95 to find the test statistic of the quantile cointegration model. Furthermore, to test the causality among variables' conditional distributions, hence, to check whether the information regarding the relationships between variables could help the decision-making process, the Granger causality test (Granger, 1969) was incorporated.

We used the QQ approach (Sim & Zhou, 2015), which enables one to examine the effect of quantiles of the explanatory variable on the quantiles of the other variable, thus providing more comprehensive information compared to conventional models. The QQ approach generalizes the standard quantile regression method (Koenker & Bassett, 1978). More specifically, it is a combination of quantile

regression and nonparametric estimations. First, quantile regression is used to find the effects of the independent variable on the quantiles of the dependent variable. Second, local linear regression (Stone, 1977; Cleveland, 1979) is utilized to find a linear regression locally around the neighborhood of each data point in the sample by giving more weights to closer neighbors.

We start with the following nonparametric quantile regression equation:

$$\text{Spot}_t = \beta^\theta (\text{Futures}_t) + U_t^\theta \quad (1)$$

where  $\text{Spot}_t$  denotes the spot market returns of a given commodity in period  $t$ ,  $\text{Futures}_t$  represents the futures market returns for that commodity in period  $t$ ,  $\theta$  is the  $\theta$ th quantile of the conditional distribution of the spot returns, and  $U_t^\theta$  is a quantile error term whose conditional  $\theta$ th quantile is equal to zero.  $\beta^\theta(\cdot)$  is an unknown function because we have no prior information about the nexus between spot and futures returns.

Although quantile regression enables us to explore the varying effects of futures market returns on conditional quantiles of spot market returns, it doesn't consider the effects of quantiles of futures returns on spot returns. Hence, it doesn't provide information about the relationship between spot and futures returns when there are largely positive or negative shocks in the futures market that may also affect the OHR. To capture the relationship between the  $\theta$ th quantile of spot returns and  $\tau$ th quantile of the futures returns represented by  $\text{Futures}^\tau$ , Eq. (1) is examined in the neighborhood of the  $\text{Futures}^\tau$  by utilizing the local linear regression. We can expand  $\beta^\theta(\cdot)$  with the first-order Taylor expansion around a quantile of  $\text{Futures}^\tau$  with the help of the following equation:

$$\beta^\theta (\text{Futures}_t) \approx \beta^\theta (\text{Futures}^\tau) + \beta^{\theta,\tau} (\text{Futures}^\tau) (\text{Futures}_t - \text{Futures}^\tau) \quad (2)$$

where  $\beta^{\theta,\tau}$  is the partial derivative of  $\beta^\theta (\text{Futures}_t)$  with respect to  $\text{Futures}^\tau$ , which is the marginal response. This coefficient has a similar interpretation as the slope coefficient in a linear regression framework. The main feature of Eq. (2) is that it considers both  $\theta$  and  $\tau$  as doubled indexed parameters that are illustrated as  $\beta^\theta(\text{Futures}^\tau)$  and  $\beta^{\theta,\tau}(\text{Futures}^\tau)$ . Moreover,  $\beta^\theta(\text{Futures}^\tau)$  and  $\beta^{\theta,\tau}(\text{Futures}^\tau)$  are both functions of  $\theta$  and  $\text{Futures}^\tau$  and  $\text{Futures}^\tau$  is a function of  $\tau$ . Thus  $\beta^\theta(\text{Futures}^\tau)$  and  $\beta^{\theta,\tau}(\text{Futures}^\tau)$  are both functions of  $\theta$  and  $\tau$ . It is also possible to rename  $\beta^\theta(\text{Futures}^\tau)$  and  $\beta^{\theta,\tau}(\text{Futures}^\tau)$  as  $\beta_0(\theta,\tau)$  and  $\beta_1(\theta,\tau)$ , respectively. Based on that, the modified version of eq. (2) can be rewritten as:

$$\beta^\theta (\text{Futures}_t) \approx \beta_0 (\theta,\tau) + \beta_1 (\theta,\tau) (\text{Futures}_t - \text{Futures}^\tau) \quad (3)$$

We derive Eq. (4) by substituting Eq. (3) in Eq. (1):

$$\text{Spot}_t = b_0 (q,t) + b_1 (q,t) (\text{Futures}_t - \text{Futures}_t) + U_t^q \quad (4)$$

(\*)



The part (\*) in eq. (4) represents the  $\theta$ th conditional quantile of the spot returns. However, since  $\beta_0$  and  $\beta_1$  are dual indexed in  $\theta$  and  $\tau$ , (\*) shows the relationship between the  $\theta$  quantile of spot returns and  $\tau$  quantile of futures returns. Next,  $\text{Futures}_t$  and  $\text{Futures}_\tau$  need to be replaced by their estimated counterparts  $\widehat{\text{Futures}}_t$  and  $\widehat{\text{Futures}}_\tau$  in Eq. (4) so that the local linear regression estimation of the parameters  $\beta_0$  and  $\beta_1$ , which are  $b_0$  and  $b_1$  can be obtained through minimizing the following equation:

$$\min_{b_0, b_1} \sum_n^{i=1} r_q \left[ \text{Spot}_t - b_0 - b_1 \left( \widehat{\text{Futures}}_t - \widehat{\text{Futures}}_\tau \right) \right] \times K \left( \frac{F_n \left( \widehat{\text{Futures}}_t \right) - t}{h} \right) \quad (5)$$

Where  $\rho_\theta$  is the quantile loss function, interpreted as  $\rho_\theta(u) = u(\theta - I(u < 1))$ ;  $I$  is the usual indicator function;  $K(\cdot)$  represents the Kernel function, and the parameter  $h$  in the denominator is the bandwidth of the Kernel.

To weigh the observations in the neighborhood of  $\widehat{\text{Futures}}_\tau$ , we used the Gaussian Kernel function. Gaussian Kernel is symmetric around zero and therefore assigns the least weights to observations farther away. Moreover, there is an inverse relationship between these weights and the distance of the observations among the distribution function of  $\widehat{\text{Futures}}_\tau$ , defined by:

$$F_n \left( \widehat{\text{Futures}}_\tau \right) = \frac{1}{n} \sum_n^{k=1} I \left( \widehat{\text{Futures}}_k < \widehat{\text{Futures}}_\tau \right)$$

and eventually generates the value from the distribution function corresponding to the  $\widehat{\text{Futures}}_\tau$ , representing as  $\tau$ .

The bandwidth parameter in Kernel function is one of the most important factors as it represents the size of the neighborhood around the target point in which choosing a large number for  $h$  can lead to estimation bias, and a small number can generate a greater variance in our estimation. In this study, we set the bandwidth parameter as  $h = 0.09$ .

## Empirical Findings

In Table 3, the results of the quantile cointegration are reported. Tabulated results confirm the long-run relationship between oil, natural gas, and gasoline spot and four futures contract returns. Therefore, they show that the variations among the coefficients vary throughout the quantiles of the variables. The critical values generated by 1000 Monte Carlo simulations in which CV1, CV5, and CV10 are the critical values for the significance level of 0.01, 0.05, and 0.1, respectively.

We provide the Quantile Granger Causality test results in Table 4. Probability values for the test statistics indicate that for all these energy market commodities,

**Table 3** Quantile cointegration test results

Model	Coeff.	Sup <sub>τ</sub>   V <sub>θ</sub> (τ)	CV1	CV5	CV10
<i>OIL vs. Futures (OIL)</i>					
OIL <sub>t</sub> vs. Futures-1 <sub>t</sub>	β	4831.288***	3715.224	3089.316	2831.001
	γ	1537.026***	1102.441	896.315	715.308
OIL <sub>t</sub> vs. Futures-2 <sub>t</sub>	β	59,463.215***	46,318.157	34,361.058	23,135.251
	γ	18,302.088***	16,328.048	13,841.554	10,846.213
OIL <sub>t</sub> vs. Futures-3 <sub>t</sub>	β	3460.587***	2893.046	2147.315	1836.149
	γ	1635.548***	1205.687	951.089	831.356
OIL <sub>t</sub> vs. Futures-4 <sub>t</sub>	β	230.006*	349.010	239.887	133.041
	γ	143.353*	259.703	155.975	105.115
<i>NGAS vs. Futures (NGAS)</i>					
NGAS <sub>t</sub> vs. Futures-1 <sub>t</sub>	β	2974.368***	2204.007	1346.648	593.872
	γ	1815.187***	1345.054	821.828	362.426
NGAS <sub>t</sub> vs. Futures-2 <sub>t</sub>	β	3089.004***	2288.952	1398.550	616.760
	γ	1189.146***	881.157	538.387	237.429
NGAS <sub>t</sub> vs. Futures-3 <sub>t</sub>	β	4899.108***	3630.239	2218.076	978.172
	γ	1960.387***	1452.647	887.567	391.417
NGAS <sub>t</sub> vs. Futures-4 <sub>t</sub>	β	6571.316***	4869.345	2975.170	1312.050
	γ	2502.894***	1854.644	1133.188	499.736
<i>RBOB vs. Futures (RBOB)</i>					
RBOB <sub>t</sub> vs. Futures-1 <sub>t</sub>	β	7328.842***	5430.672	3318.141	1463.300
	γ	4472.620***	3314.212	2024.984	893.018
RBOB <sub>t</sub> vs. Futures-2 <sub>t</sub>	β	7611.305***	5639.978	3446.026	1519.698
	γ	2930.055***	2171.171	1326.586	585.024
RBOB <sub>t</sub> vs. Futures-3 <sub>t</sub>	β	12,071.402***	8944.909	5465.339	2410.215
	γ	4830.393***	3579.322	2186.966	964.452
RBOB <sub>t</sub> vs. Futures-4 <sub>t</sub>	β	16191.722**	19,998.066	7330.819	3232.891
	γ	6167.130**	7569.844	2792.175	1231.349

Note: This table presents the results of the quantile cointegration test of Xiao (2009) for the logarithm of the Oil price, natural gas, gasoline, and all proxies of the Futures market. CV1, CV5, and CV10 are the critical values of statistical significance at 1%, 5%, and 10%, respectively. We use 1000 Monte Carlo simulations to generate critical values. We use an equally spaced grid of 19 quantiles, [0.05–0.95], to calculate the test statistic of the quantile cointegration model

there is bidirectional Granger causality between the spot market and 1, 2, 3, and 4 months’ futures contracts. This finding is relevant for all the quantiles, which shows that the relationship between spot and futures returns is persistent for each point of the distribution of the variables. Hence, it is possible to employ the data for the spot (futures) market to make better predictions about the futures (spot) returns. Either upward or downward movements in spot returns and futures returns promulgate the movements in each other.

Figure 1a–l illustrates the QQ relationship and estimates the slope coefficient  $\beta_1(\theta, \tau)$ , which captures the effect of futures  $\tau$ th quantile return on the  $\theta$ th quantile return of the spots at different values of  $\tau$  and  $\theta$  of three energy market commodities under investigation. Four exciting results emerged from the figures. First, all the

**Table 4** Results of Granger Causality in quantiles

Quantiles	[0.05-0.95]	0.05	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	0.95
$\Delta OIL_t \rightarrow \Delta FUT1_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta OIL_t \leftarrow \Delta FUT1_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta OIL_t \rightarrow \Delta FUT2_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta OIL_t \leftarrow \Delta FUT2_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta OIL_t \rightarrow \Delta FUT3_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta OIL_t \leftarrow \Delta FUT3_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta OIL_t \rightarrow \Delta FUT4_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta OIL_t \leftarrow \Delta FUT4_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \rightarrow \Delta FUT1_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \leftarrow \Delta FUT1_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \rightarrow \Delta FUT2_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \leftarrow \Delta FUT2_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \rightarrow \Delta FUT3_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \leftarrow \Delta FUT3_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \rightarrow \Delta FUT4_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta NGAS_t \leftarrow \Delta FUT4_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \rightarrow \Delta FUT1_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \leftarrow \Delta FUT1_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \rightarrow \Delta FUT2_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \leftarrow \Delta FUT2_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \rightarrow \Delta FUT3_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \leftarrow \Delta FUT3_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \rightarrow \Delta FUT4_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\Delta ARBOB_t \leftarrow \Delta FUT4_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' estimation

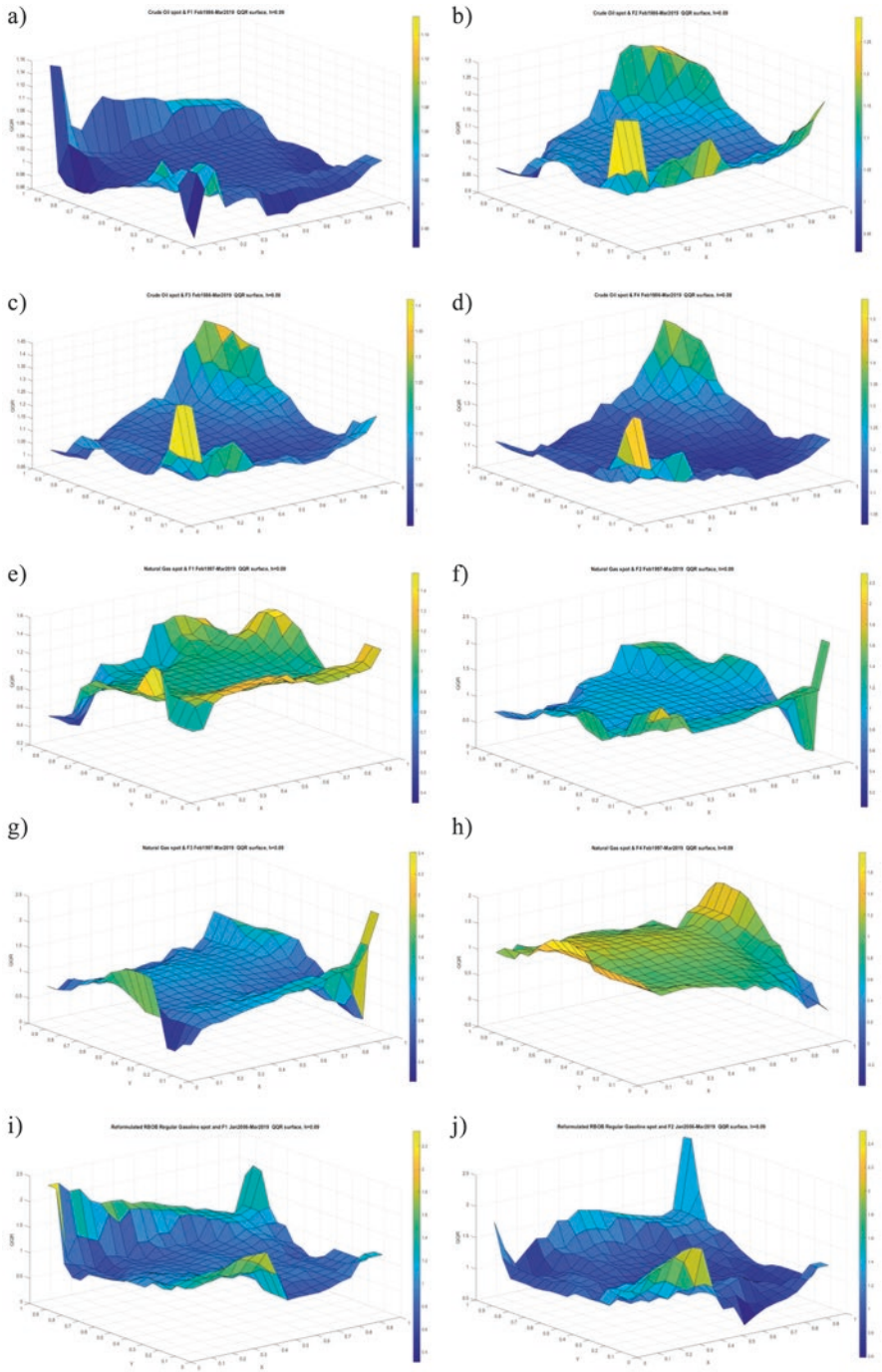


Fig. 1 Quantile-on-Quantile 3-D surface view

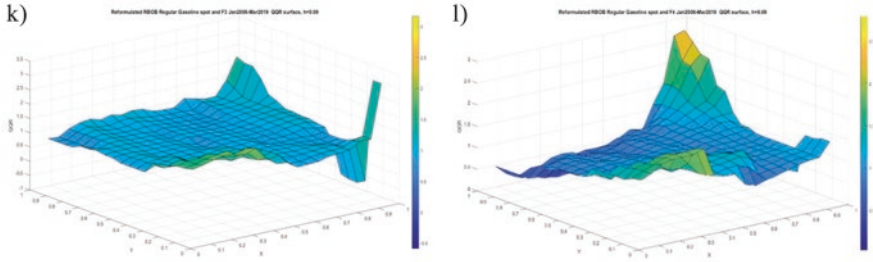


Fig. 1.1 (continued)

figures show a positive relationship for the entire quantiles of spot and futures returns for all commodities. This result is consistent with the positive nexus between spot and futures market that has been documented by the prior literature, and it sheds light on the fact that the futures market plays a vital role in price discovery (Shrestha, 2014; Chang & Lee, 2015; Shrestha et al., 2018). Second, we observed heterogeneity across crude oil, gasoline, and natural gas regarding the association between spot and futures returns. Third, there are considerable variations in the OHR across the distributions of spot and futures returns for all three commodities. This result suggests that across quantiles, the relationship between spot and futures return is not uniform, but this relationship depends on the size and sign of futures market shocks and, at the same time, the particular states of the spot market. Additionally, we found the most variations of the OHR for three commodities at the highest and the lowest quantiles of the spot and futures returns distributions, that is, when there are extreme events in the spot and futures market. Finally, as the time to maturity in futures contracts increases, the fluctuations in the OHR decrease considerably. The mentioned result shows that a three to four-month time span is enough for spot prices to converge to future prices, and the new information is reflected in the crude oil, natural gas, and gasoline market.

Among the three commodities investigated, we observed the lowest variation in the OHR for the natural gas market. Figure 1e–h shows the results generated from the QQ approach for natural gas spot returns and 1, 2, 3, and 4 months’ futures returns, respectively. We found positive and close to one OHR for medium quantiles (the central points of the distributions) for both variable distributions for all maturities of futures contracts. However, the OHR tends to strengthen or weaken at the highest or lowest quantiles of the spot and futures returns. For instance, the OHR is significantly lower than one at the highest quantiles (0.7–0.9) of the spot and lowest quantiles (0.1–0.2) of the futures market. The results are the opposite at low quantiles (0.1–0.2) of the spot and high quantiles (0.7–0.9) of the futures market. The OHR is significantly higher than one at high quantiles of both spot and futures returns (0.7–0.9), which corresponds to the bullish spot market and a futures market that experienced a large positive shock. Finally, natural gas graphs became smoother as we shift from one-month time to maturity to four-months’ time to maturity.

In the case of crude oil, Fig. 1a–d illustrates spot returns distributions for 1, 2, 3, and 4 months’ futures returns, respectively. The OHR is positive and close to one for the combination of medium quantiles (0.4–0.6) of both variables. Nevertheless, we

observed a significant variation in the OHR at the extreme quantiles. More precisely, we found that the OHR is higher than one at the lowest quantiles (0.1–0.3) of both spot and futures returns, that is, when the spot market is bearish and when there is a large negative shock in the futures market. However, we observed notably low values of the OHR in the area that combines high quantiles of spot returns (0.7–0.9) with low quantiles of futures returns (0.1–0.3). The OHR is higher than one at relatively low quantiles of spot returns (0.1–0.3) and high tails of futures returns (0.8–0.9). The highest value of the OHR was found at intermediate to high quantiles (0.6–0.9) of both spot and futures returns, which corresponds to the combination of a bullish spot market and positive shock in the futures market. Again, as we move from 1 month to maturity futures contracts to longer maturities, we observe smoother changes and a lower OHR variation for crude oil.

For gasoline, Fig. 1i–l shows that high variation in the OHR is mostly at the highest and lowest quantiles of the spot and futures returns. Similar to the natural gas and crude oil graphs, the OHR for the gasoline market is close to one when the spot and futures market condition is normal; which is, at medium quantiles of spot and futures returns (0.4–0.6). The changes in the OHR are more prominent at higher quantiles. We observed that the OHR is significantly higher than one at the intermediate to upper quantiles of both variables (0.7–0.9). In the case of a bearish spot market (0.1–0.3) and large adverse shocks in the futures market (0.1–0.3), the OHR is higher than one, but not as strong as the highest quantiles of both variables. At the high tails of the spot (0.7–0.9) and low tails of futures returns (0.1–0.3), OHR is higher. However, this effect flattens out as the time to maturity of the futures contract gets longer. These results indicate that the hedging strategy should be adjusted according to the change in spot market states and whether there are positive or negative shocks in the futures market.

The QQ approach decomposes the findings of the standard quantile regression. In this paper, we regressed the  $\theta$  quantiles of the spot market returns on the futures market returns using the quantile regression model. Thus, the estimates of the quantile regression parameters are only indexed by the  $\theta$ . Although, as we mentioned in the methodology part, the QQ approach regresses the  $\theta$ th quantile of the spot returns on the  $\tau$ th quantile of the futures returns. Thus, we can consider  $\theta$  and  $\tau$  as indexes for QQ approach parameters. It is possible to recover the estimates of the quantile regression by taking the average of the QQ coefficients along  $\tau$ . As an example, the slope coefficient of the standard quantile regression method, which captures the effect of futures returns on the distribution of the spot returns and is denoted  $\gamma_1(\theta)$  can be generated as follows:

$$\gamma_1(\theta) \equiv \hat{\beta}(\theta) = \frac{1}{S} \sum_{\tau} \hat{\beta}(\theta, \tau)$$

where  $S = 19$  is the number of quantiles  $\tau = [0.05, 0.10, \dots, 0.95]$  considered.

In this regard, one way to check the QQ approach's validity is to compare the estimates obtained by taking the averages of the QQ coefficients with those of the standard quantile regression model. Figure 2a–l illustrates that the averaged QQ

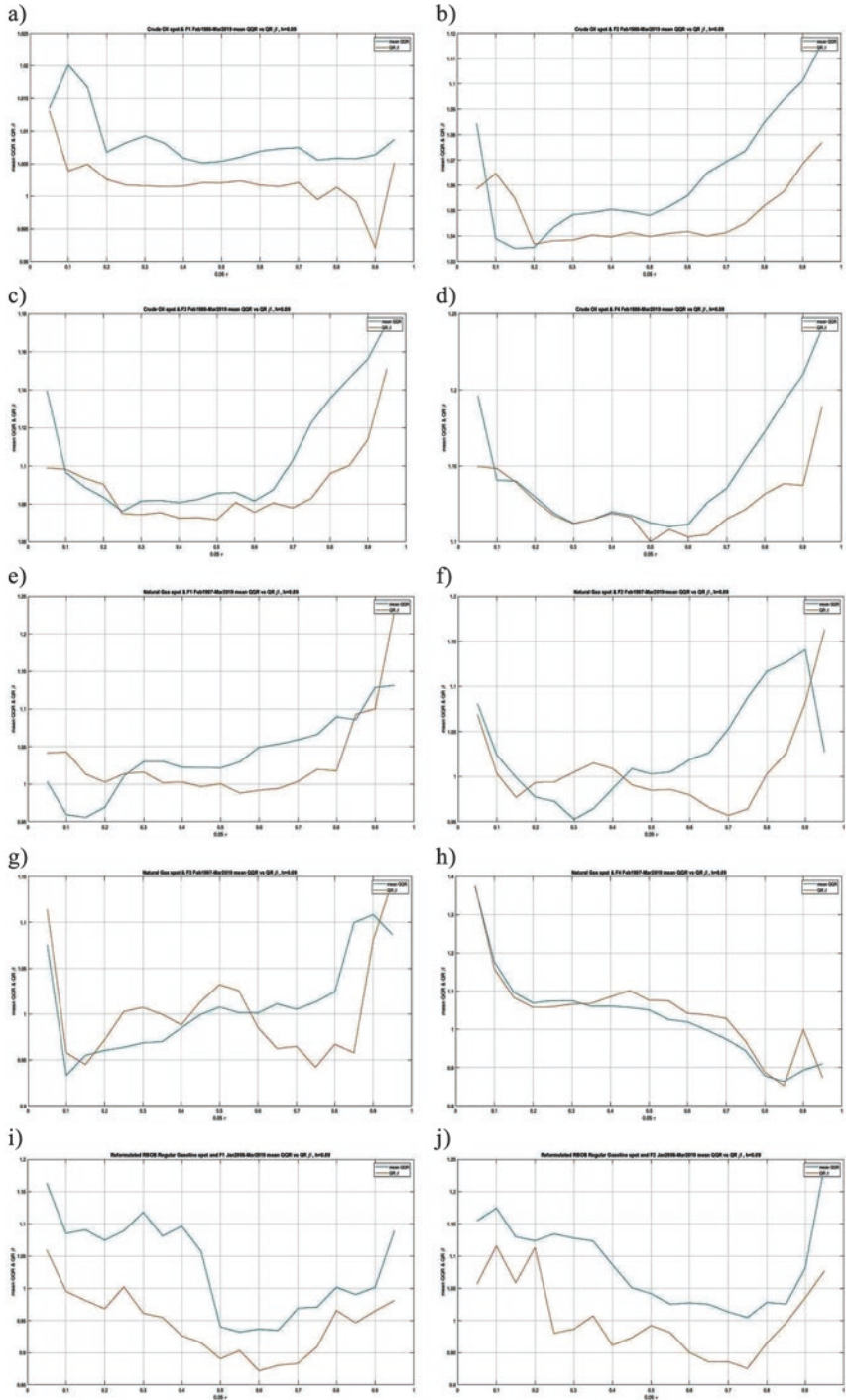


Fig. 2 Comparison of quantile regression and QQ estimates

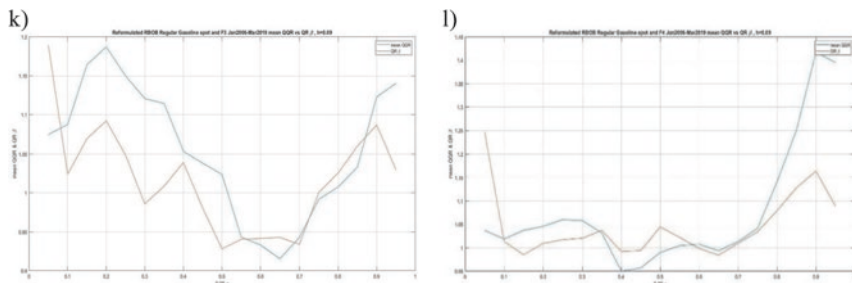


Fig. 1.2 (continued)

estimates and the quantile regression estimates are quite identical for all three variables. Referring to these graphs, we can provide validation for the QQ findings by showing that it is possible to recover the estimates of the quantile regression by taking the averages of the parameters estimated from the QQ approach.

## Conclusion and Policy Implications

This study empirically examined the long-run and causal relationship and the OHR between spot and futures prices for crude oil, natural gas, and gasoline. In contrast to most previous empirical studies, we consider the distribution of variables under investigation. Obtained findings confirm the long-run and causal relationship among the variables, although coefficients and significance levels differ among different quantiles of the variables. Our empirical evidence highlights that the OHR can significantly vary across the distribution of spot and futures prices. According to the results, the OHR is higher than the one-to-one naive hedge ratio at high quantiles of both spot and futures prices for all three commodities. Obtained findings also confirmed the decrease in the OHR variation as the time to maturity in futures contracts increased from 1 month to 4 months. This result indicates that 4 months is long enough for spot prices to reflect the new information in the futures market.

Our findings indicate that hedging strategy should be calibrated due to the change in spot market states and when there are positive or negative shocks in the futures market. The findings of this study are valuable for policymakers, portfolio managers, and companies. These agents should know the variation of the OHR at different spot and futures market conditions such as bullish, bearish, contango, and backwardation and also at the entire market distributions for a more efficient diversification and policy formation. The empirical results are beneficial for portfolio managers as they provide clear and comprehensive information about the linkage between spot and futures prices so that managers can reduce the risk associated with the portfolio under management using futures contracts. In particular, energy market companies can take advantage of our findings through the pattern of dynamic hedge ratios among spot and futures prices. During the different market states, they need



to follow dynamic hedging strategies and change their positions accordingly. In the case of practitioners involved in the energy market, it is crucial to know how to modify their derivatives market positions to avoid adverse price movements. They should consider that for the shorter time to maturities, the hedge ratio is significantly dependent on the quantiles of both spot and futures prices. However, this dependency flattens out for longer futures contract maturities such as 3 and 4 months. For instance, during the extreme spot market condition, and when there is a large positive shock in the futures market, they need to increase their short position in the futures market compared with their commodity holding. Furthermore, policymakers can benefit from this study, as our results show the critical role of the futures market in price discovery. However, this role can vary according to the change in the commodity.

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