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Revisiting Crude Oil Price and China's Stock Market*

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In this paper, we propose a two-step nonlinear quantile causality test approach to investigate the bidirectional relationship between oil price return and China's stock price return using daily data of West Texas Intermediate crude oil prices and Shanghai Stock Exchange index for a period from January 1, 2001, to November 2, 2015. Although we cannot observe a significant linear causality, our results show that there are significant bidirectional causality correlations between oil price return and stock price return in the low quantiles.

Key Words: Crude Oil Prices; Stock Prices; Causality; Quantile Regression.
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1. INTRODUCTION

Since the turn of the century, exactly whether, and if so the extent of how crude oil price correlate with stock market raises many important contentions. Literature in this terrain keeps growing and reveals a sharp increase along with dramatic fluctuation of energy prices especially around the recession in 2008.[1] Compared with few researches denied the interdependence between crude oil prices and stock prices, their substantial relationship has generally been observed no matter in developed countries (Papapetrou (2001), Park and Ratti (2008), Miller and Ratti (2009), Filis (2010)) or in emerging markets (Basher and Sadorsky (2006), Masih et al. (2011)).[2] However, existence of interaction of the two aggregate markets indices in China is often challenged due to China's unique pricing mechanism of oil products and high speculativeness and intransparency of its stock market.[3] For example, by employing multivariate vector autoregression, Cong et al. (2008) argue that oil price shocks do not show statistically significant impact on the real stock returns of most Chinese stock market indices with the exception of manufacturing index and some oil companies. Fang and You (2014) similarly claim that the impact of oil prices shocks on stock prices in China is insignificant due to segmentation of China's stock market from others. Broadstock and Filis (2014) pointed out that, differing from the US counterpart, the Chinese stock market did not seem to be particularly influenced from the international oil market between 1998 and 2007.

As Broadstock et al. (2012) point out, researches investigating relationship between international oil price and stock market behavior in China are still limited despite of its role as the second largest oil consumer and the second largest stock market China owns. To further analyze the relationship between oil prices and stock prices, we firstly perform a linear causality test. Several unit root tests are employed to confirm that two price series have unit roots and their returns are stationary, due to the prerequisite requirement for stable series in linear causality model. It is shown that no linear causality between Shanghai Stock Exchange (SSE) price return and West Texas Intermediate (WTI) oil price return existed. Then we detect the existence of nonlinear causality relation between the two by using a non-parameter causality test and get a positive outcome.

[1] There still exist some pioneer researches done by Jones and Kaul (1996), Huang et al. (1996) and Sadorsky (1999) in 1990s.

[2] For example, Huang et al. (1996) and Apergis and Miller (2009) between crude oil prices and stock prices

[3] The refined oil price in China does not automatically adjusted in response to international oil prices. In fact, it is less frequently adjusted by National Development and Reform Committee in Central government, and consequently becomes less volatile compared with those in other countries.

Lastly, we propose a nonlinear quantile causality test approach to investigate the bidirectional causal relationship between oil price return and China's stock price return, since little attention has been paid to reverse causality from stock market to crude oil market in prior analyses. We find that there are significant bidirectional causality correlations between the two in the low quantiles. Specifically, SSE price return significantly correlates with WTI price return only when WTI price return is relatively low (quantile 0.05-0.2 and 0.2-0.4), and WTI price returns also significantly co-move with SSE price return only when SSE is relatively low. The effect might roots in that, as Baur and Schulze (2005) and Ding et al. (2014) argue, systemic risk arises under extreme market conditions. When the return of the stock market is extremely low, it becomes more sensitive to the shock of oil market, and vice versa. The high sensitivity of stock price in extreme situation might be influenced by sentiment of investors who is disproportionately more sensitive to bad news rather than good news in stock market. Dramatic decrease of oil price is easily to be read as signal for recessive economy (Hamilton (1983). That is to say, a fall in oil price forms a bad news in predicting economic performance and accordingly affects investors' willingness to invest in stock market. The stock price returns, as a result, asymmetrically co-move with the oil price fluctuation in low prices arena. This is consistent with Chen and Lv (2015) who claims a dramatically increased dependence level between the world oil market and the Chinese Stock market during the crisis period, i.e. a period with extreme systemic risk, but that the simultaneous booms between these two markets decrease considerably after the crisis.[4]

The rest of the paper is arranged as follows. In Section 2, we conduct empirical tests for both linear and nonlinear causalities of WTI crude oil prices and SSE index for a period from January 1, 2001, to November 2, 2015. Then we make our conclusion in Section 3.

2. EMPIRICAL ANALYSIS

2.1. Linear and Nonlinear Causality test

In this section, we analyze the relationship between WTI oil prices and SSE index through applying linear and nonlinear causality test. First we test the null hypothesis that there is a linear causality between WTI oil prices and SSE index following traditional Granger causality test. This can be done empirically using a bivariate autoregressive model for two stationary series in a two equations model:

[4]Differing from their judgment, our finding is generally applicable when both lie in low quartiles rather than merely fits a certain time period.

$$\begin{aligned} X_t =& a_1 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_{1t} \\ Y_t =& a_2 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + \varepsilon_{2t} \end{aligned} \tag{1}$$

where ε_{1t}, ε_{2t} are the disturbance terms obeying the assumptions of the classical linear normal regression model. Y_t does not Granger cause X_t if and only if $\beta_i = 0$, for all i. Similarly, X_t does not Granger cause Y_t if and only if $\gamma_i = 0$, for all i. To test the null hypothesis of no causality, the standard F test may be used. For example, to test $\beta_i = 0$ for all i, the F test is like as follows.

$$F = \frac{(SSR_R - SSR_F)/p}{SSR_F/(n-2p-1)} \tag{2}$$

where SSR_R and SSR_F are the sums of square of residuals for the restricted regression and the full regression, respectively. p is the number of lag terms of Y_t in the regression equation on X_t, and n is the number of observations. If Y_t does not Granger cause X_t, F is distributed as $F_{(p,n-2p-1)}$. For given significance level α, the null hypothesis is rejected if F exceeds the critical value $F_{(\alpha,p,n-2p-1)}$. Testing $\gamma_i = 0$ for any i is similar.

In our paper, daily data of West Texas Intermediate oil price and Shanghai Stock Exchange index are used as price benchmarks for crude oil markets and Chinese stock markets. Figure 1 plots WTI/SSE price and return from January 1, 2001, to November 2, 2015. As shown in Figure 1, WTI oil price and SSE index are relatively stable before 2007 but start to increase and peak in the summer of 2008 and in the end of 2007 respectively.

Similar to macroeconomic aggregate variables such as real GDP, stock and oil prices exhibit trending behaviors or nonstationary in mean. As such, we conduct three unit root tests and a stationarity test. For the unit root tests, we consider the augmented Dickey-Fuller (ADF, Dickey and Fuller, 1981), Dickey-Fuller generalized least squares (DF-GLS, Elliott, Rothenberg, and Stock, 1996), and Phillips-Perron (PP, Phillips and Perron, 1988) tests. In these tests, the null hypothesis is that the series has a unit root. For the stationarity test, we consider the Kwiatkowski, Phillips, Schmidt and Shin (KPSS, Kwiatkowski, Phillips, Schmidt and Shin, 1992) test, whose null is that the series is stationary. Table 1 shows that both WTI and SSE have a unit root, and are stationary after first difference. If the series contains a unit root, then the standard assumptions for an asymptotic analysis are not valid. In this regard, we consider the return of WTI and SSE instead of stock price of WTI and SSE to

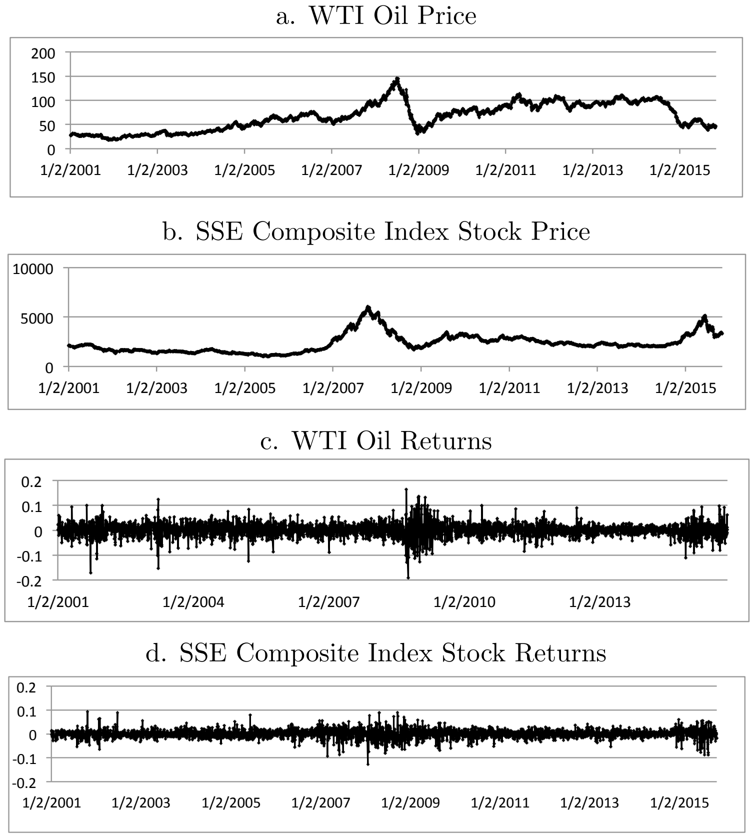

FIG. 1. Time Series Data: Prices and Returns

test the linear causality between WTI and SSE, and the equations are depicted as followed:

$$
\begin{aligned}
\Delta WTI_t =& a_1 + \sum_{i=1}^{p} \alpha_i \cdot \Delta WTI_{t-i} + \sum_{i=1}^{p} \beta_i \cdot \Delta SSE_{t-i} + \varepsilon_{1t} \\
\Delta SSE_t =& a_2 + \sum_{i=1}^{p} \gamma_i \cdot \Delta WTI_{t-i} + \sum_{i=1}^{p} \delta_i \cdot \Delta SSE_{t-i} + \varepsilon_{2t}
\end{aligned}
\tag{3}
$$

where ΔWTI_t and ΔSSE_t refer to the return of WTI and SSE stock price.

Table 2 shows the results of linear Granger causality tests for return of oil price and shanghai stock index. We select the optimal lag truncation order

TABLE 1.

Unit Root Test

	ADF	DF-GLS	PP	KPSS	Stationary [Y/N]
WTI	-1.324	-1.820	-1.415	1.03^{***}	N
	[6]	[21]	[9]	[29]	
$r.WTI$	-22.130^{***}	-4.220^{***}	-61.857^{***}	0.047	Y
	[8]	[29]	[9]	[29]	
$d.WTI$	-23.224^{***}	-7.112^{***}	-63.120^{***}	0.053	Y
	[6]	[29]	[9]	[29]	
SSE	-1.924	-2.049	-1.879	0.647^{***}	N
	[6]	[28]	[9]	[29]	
$r.SSE$	-20.148^{***}	-4.577^{**}	-58.433^{***}	0.095	Y
	[10]	[29]	[9]	[29]	
$d.SSE$	-22.986^{***}	-5.780^{***}	-58.113^{***}	0.068	Y
	[5]	[28]	[8]	[29]	
c.v. 1%	-3.960	-3.480	-3.960	0.216	
c.v. 5%	-3.410	-2.841	-3.410	0.146	
c.v. 10%	-3.120	-2.553	-3.120	0.119	

Notes: Numbers in square brackets are selected lags. ADF, DF-GLS and PP are, respectively, augmented Dickey-Fuller, Dickey-Fuller generalized least squares and Phillips-Perron statistics for the null hypothesis of a unit root for the time series. KPSS denotes the stationary test for the null hypothesis of stationarity. *, **, *** represent 10%, 5%, 1% significant level separately. $WTI/d.WTI$ is level/first difference of daily oil price, and $SSE/d.SSE$ is level/first difference of daily Shanghai Stock Exchange index. $r.WTI$ and $r.SSE$ are return of oil and Shanghai stock price. The entry "Y" indicates that the null hypothesis of having a unit root is rejected at the 5% level, whereas the entry "N" indicates that the null hypothesis could not be rejected at the 5% level.

based on the Akaike Information Criterion. The estimation results in Table 2 show that we cannot reject the null hypotheses that WTI return and SSE return do not have the linear predictive power to each other. These results seem to be inconsistent with the conclusion of previous studies on other countries in most of which substantial relationship between oil return and stock return are confirmed. Two possible reasons might account for the inconsistency. The first possibility is that WTI does not Granger cause SSE and vice versa. As Fang and You (2014) argue, newly industrialized economies' stock markets such as SSE are partially integrated with the other stock markets and oil price shocks, and the relation between their stock markets and oil price could be different from the effects on the U.S. and developed countries' stock markets. Moreover, due to the special pricing regulation, the refined oil price in China is less frequently adjusted by government, and consequently becomes less volatile compared with those in other countries. The second possibility is that the causal relation is not linear thus cannot be detected by traditional Granger causality test. Many scholars argue that oil price shocks have asymmetric effects on macroeconomics variables, which may shed lights on the effects of oil prices shock on the domestic stock market (see Hamilton (1983), Mork (1989)). Therefore, it motivates us to conduct a test for the existence of a nonlinear causality between WTI and SSE by utilizing a nonlinear causality test following Hiemstra and Jones (1994).

TABLE 2.

Linear and Nonlinear Granger Causality Test

Null Hypothesis	p-value	Causality or not
$r.SSE$ does not Grange casue $r.WTI$	0.4372	N
$r.WTI$ does not Grange casue $r.SSE$	0.1166	N
$r.SSE$ does not nonlinearly Grange casue $r.WTI$	0.0083	Y
$r.WTI$ does not nonlinearly Grange casue $r.SSE$	0.0484	Y

Notes: WTI is level of daily oil price, and SSE is level of daily Shanghai Stock Exchange index. $r.WTI$ and $r.SSE$ are return of oil and Shanghai stock price. p-value of statistics are reported in the table. The entry "N" indicates that the null hypothesis of no linear Granger causality could not be rejected at the 5% level, and the entry "Y" indicates that the null hypothesis of no nonlinear Granger causality is rejected at the 5% level.

According to the definition of causality proposed by Granger (1969), the causal relationship between two time series variables could be nonlinear as well. As originally specified, the random variable Y_t does not Granger-cause the random variable $X_t, t = 1, 2, \ldots$ if:

$$\begin{aligned} &Pr(\|X_t^m - X_s^m\| < e | \|X_{t-L_x}^{L_x} - X_{s-L-x}^{L_x}\| < e,\ \|Y_{t-L_y}^{L_y} - Y_{s-L_y}^{L_y}\| < e) \\ =&Pr(\|X_t^m - X_s^m\| < e | \|X_{t-L_x}^{L_x} - X_{s-L_x}^{L_x}\| < e) \end{aligned} \tag{4}$$

where $Pr(\ )$ denotes probability distribution and $\|\ \|$ denotes the maximum norm. $m \geq 1, L_x, L_y > 1$ are given values and $e > 0$. x_t^m is the m-length lead vector of X_{it}:

$$X_t^m \equiv (X_t, X_{t+1}, \ldots, X_{t+m-1}),\ m = 1, 2, \ldots,\quad t = 1, 2, \ldots$$

$X_{t-L_x}^{L_x}$ refers to L_x-length lag vector of X_{it}:

$$X_{t-L_x}^{L_x} \equiv (X_{t-L_x}, X_{t-L_x+1}, \ldots, X_{t-1}), L_x = 1, 2, \ldots,\ t = L_x + 1, L_x + 2, \ldots$$

and $Y_{t-L_y}^{L_y}$ refers to L_y-length lag vector of Y_t:

$$Y_{t-L_y}^{L_y} \equiv (Y_{t-L_y}, Y_{t-L_y+1}, \ldots, Y_{t-1}), L_y = 1, 2, \ldots,\ t = L_y + 1, L_y + 2, \ldots$$

Here we do not use WTI and SSE return directly, but two strictly stationary and weakly dependent residual series, $\hat{\varepsilon}_{1t}$ and $\hat{\varepsilon}_{2t}$, instead, which are obtained from equation (3) and are denoted by x_t and y_t, so we can exclude the linear causal relation. Then we can detect the nonlinear causal relation between oil price and SSE Composite index. According to Baek and Brock (1992) and Hiemstra and Jones (1994), ΔSSE_t does not strictly Granger cause another series ΔWTI_t if and only if:

$$\begin{aligned} &Pr(\|x_t^m - x_s^m\|) < e \| \|x_{t-L_x}^{L_x} - x_{s-L_x}^{L_x}\| < e, \|y_{t-L_y}^{L_y} - y_{s-L_y}^{L_y}\| < e) \\ =&Pr(\|x_t^m - x_s^m\| < e \| \|x_{t-L_x}^{L_x} - x_{s-L_x}^{L_x}\| < e) \end{aligned} \tag{5}$$

where x_t and y_t are the residuals. In our paper, $m = 1, L_x = L_y = 10, e = 1.5$.

Let $C1(m_x+L_x, L_y, e, n)/C2)L_x, L_y, e, n$ and $C3(m_x+L_x, e, n)/C4(L_x, e, n)$ denote the ratios of joint probabilities corresponding to the left side and right side of equation (5). Correlation-integral estimators of the joint probabilities can be written as:

$$\begin{aligned} C1(m+L_x, L_y, e, n) &\equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-L_x}^{m+L_x}, x_{s-L_x}^{m+L_x}, e\right) \cdot I\left(y_{t-L_y}^{L_y}, y_{s-L_y}^{L_y}, e\right) \\ C2(L_x, L_y, e, n) &\equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-L_x}^{L_x}, x_{s-L_x}^{L_x}, e\right) \cdot I\left(y_{t-L_y}^{L_y}, y_{s-L_y}^{L_y}, e\right) \\ C3(m+L_x, e, n) &\equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-L_x}^{m+L_x}, x_{s-L_x}^{m+L_x}, e\right) \\ C4(L_x, e, n) &\equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-L_x}^{L_x}, x_{s-L_x}^{L_x}, e\right) \end{aligned}$$

and

$$I(x, y, e) = \begin{cases} 0, & \text{if } \|x - y\| > e \\ 1, & \text{if } \|x - y\| \le e \end{cases}$$

$$t, s = \max(L_x, L_y) + 1, \ldots, T - m + 1, \quad n = T + 1 - m - \max(L_x, L_y)$$

Under the assumptions that x_t and y_t are strictly stationary, weakly dependent, and satisfy the mixing conditions of Denker and Keller (1983), if y_t does not strictly Granger cause x_t, then the test statistic:

$$\sqrt{n}\left(\frac{C1(m+L_x, L_y, e, n)}{C2(L_x, L_y, e, n)} - \frac{C3(m+L_x, e, n)}{C4(L_x, e, n)}\right) \sim N\left(0, \sigma^2(m, L_x, L_y, e)\right) \tag{6}$$

And an estimator of the variance $\sigma^2(m, L_x, L_y, e)$ has been provided by Hiemstra and Jones (1994).

As shown in Table 2, the bidirectional causal relation between return of WTI and SSE is significant at 5% level, and this relation between first difference of WTI and SSE is even significant at 1% level. WTI and SSE have power to predict each other, however, such predictive power is nonlinear and asymmetric, which is unable to be detected by traditional Granger causality tests. Previous studies, according to this finding, might have overestimated difference between impact of oil price shocks on stock prices in developed markets and emerging markets, such as China. Also, interdependence between Chinese aggregate stock market and oil price has probably been ignored in some prior analysis. In the following section, we will further define "nonlinear" from the perspective of conditional quantiles. Quantiles Granger causality test is employed to discuss the nonlinear relation whether WTI/SSE would influence SSE/WTI under various conditions (e.g., a bear or bull market).

2.2. Quantiles Causality test

For a comprehensive understanding of the causal relationship between X_t and Y_t, Chuang, Kuan, and Lin (2009) consider Granger causality in quantiles:

$$Q_{Y_t}(\tau|(Y,X)_{t-1}) = Q_{Y_t}(\tau|Y_{t-1}),\ \forall\tau \in [a,b]a.s., \tag{7}$$

where $Q_{Y_t}(\tau|T)$ denotes the τ-th quantile of $F_{Y_t}(\ |T)$. If equation (7) holds, then we can say that X_t does not Granger cause Y_t over the quantile interval $[a, b]$. Granger nonlinear causality in quantiles can be tested by the quantile regression method proposed in Koenker and Bassett (1978) and Bassett and Koenker (1982). In addition the classical Granger causality test, we can consider conditional quantile versions of equation (4):

$$\begin{aligned}
Q_{Y_t}(\tau|\Delta WTI_{t-1}) =& a_1(\tau) + \sum_{j=1}^{q}\alpha_j(\tau)\cdot\Delta WTI_{t-j} + \sum_{j=1}^{q}\beta_j(t)\cdot\Delta SSE_{t-j}\\
Q_{Y_t}(\tau|\Delta SSE_{t-1}) =& a_2(\tau) + \sum_{j=1}^{q}\gamma_j(\tau)\cdot\Delta WTI_{t-j} + \sum_{j=1}^{q}\delta_j(\tau)\cdot\Delta SSE_{t-j}
\end{aligned} \tag{8}$$

Therefore, if the parameter vector $\beta(\tau) = (\beta_1(\tau), \beta_2(\tau), \ldots, \beta_q(\tau))'$ is equal to zero, then we say that ΔSSE_t does not Granger cause ΔWTI_t at the τ quantile level. Similarly, $\gamma(\tau) = (\gamma_1(\tau), \gamma_2(\tau), \ldots, \gamma_q(\tau))'$ implies that the growth rate of WTI does not Granger cause SSE composite index return at the τ quantile level. We can express the null hypothesis for Granger causality at the $\tau \in (0, 1)$ quantile level by

$$H_0 : \beta(\tau) = 0$$

For fixed $\tau \in (0,1)$, we can write the Wald statistic of $\beta(\tau) = 0$ as

$$W_T(\tau) = T\frac{\hat{\beta}_t(\tau)'\hat{\Omega}(\tau)^{-1}\hat{\beta}_t(\tau)}{\tau(1-\tau)}$$

where $\hat{\Omega}(\tau)$ denotes a consistent estimator of $\Omega(\tau)$, which is the variance-covariance matrix of $\beta(\tau)$.

However, the above Wald test only addresses causality at the fixed quantile level τ. In many cases, one may be interested in testing for causality in quantiles over some quantile intervals, say $\tau \in [a,b]$. Under suitable conditions and the null hypothesis $H_0 : \beta(\tau) = 0,\ \forall\tau \in [a,b]$, Koenker and Machado (1999) show that the Wald statistic process follows the following weak convergence:

$$W_T(\tau) \Rightarrow \left\| \frac{B_p(\tau)}{\sqrt{\tau(1-\tau)}} \right\|^2, \quad \text{for } \tau \in \Gamma$$

where $\Rightarrow$ denotes weak convergence (of associated probability measures), $B_p(\tau)$, a vector of p independent Brownian bridges, equals to $\sqrt{\tau(1-\tau)}N(0, I_p)$ in distribution and the weak limit is the sum of the square of p independent Bessel processes. Koenker and Machado (1999) suggest a sup-Wald test for the above null hypothesis. From the above results, we can write

$$\sup_{\tau\in\Gamma} W_T(\tau) \rightarrow \left\| \frac{B_p(\tau)}{\sqrt{\tau(1-\tau)}} \right\|^2$$

where $\rightarrow$ denotes convergence in distribution. By considering various $[a,b]$, we can capture the quantile range from which causal relationships arise. We simulate the critical values for various quantile ranges and report them in the Appendix.

Empirically, we consider five small quantile intervals, namely $[0:05; 0:2]$, $[0.2; 0.4]$, $[0.4; 0.6]$, $[0.6; 0.8]$ and $[0.8; 0.95]$. Following Ding et al. (2014), we conduct sup Wald test to select the lag truncation order q^* for each quantile interval. The optimal lag truncation order is selected using a sequential lag selection method[5]. For example, if the null $\beta_q(\tau) = 0$ for $\tau \in [0.05, 0.2]$ not rejected but the null $\beta_{q-1}(\tau) = 0$ for $\tau \in [0.05, 0.2]$ is rejected, then we set the desired lag order as $q^* = q - 1$ for the quantile interval $[0.05; 0.2]$. However, if no test statistic is significant over that interval, then we select the lag truncation of order 1. We calculate sup-Wald test statistics to check the joint significance of all coefficients of lagged

[5]Critical values can be seen in the Appendix.

stock returns (or lagged growth rates of oil prices) for each quantile interval. For example, if the desired lag order is q^*, then the null hypothesis is $H_0 : \beta_1(\tau) = \beta_2(\tau) = \beta_{q^*}(\tau) = 0$ for $\tau \in [0.05, 0.2]$. With the sup-Wald test statistics, we check whether there exists a significant causal relationship over this specific quantile interval.

Table 3 reports the estimated sup-Wald test statistics and the selected lag truncation order. We can observe that the SSE index have some predictive powers on the WTI oil price under certain specific conditions. As shown in Table 3, the sign is significant only if the stock price is in low tail quantile intervals $[0.05; 0.2]$ and $[0.2; 0.4]$. On the other hand, a similar pattern can also be observed when the oil price is in low tail quantile. For all other quantile intervals, the results are not significant, implying that WTI has a predictive power on Chinese financial market only when Chinese financial market is a bear market. This is consistent with Chen and Lv (2015) who claims a dramatically increased dependence level between the world oil market and the Chinese Stock market during the crisis period, i.e. a period with extreme systemic risk, but that the simultaneous booms between these two markets decrease considerably after the crisis. Baur and Schulze (2005) and Ding et al. (2014) provide further evidence by arguing that systemic risk arises under extreme market conditions. That is to say, when the return of the stock market is extremely low, it becomes more sensitive to the shock of oil market, and vice versa.

TABLE 3.

Test Results for Quantile Causality between SSE and WTI Crude Oil Return

$\tau \in$	[0.05,0.2]	[0.2,0.4]	[0.4,0.6]	[0.6,0.8]	[0.8,0.95]
		$r.SSE$ does not quantile cause $r.WTI$			
Statistics	8.8673^{**}	14.2669^{**}	1.2768	0.3725	1.0531
Lags	[1]	[3]	[1]	[1]	[1]
		$r.WTI$ does not quantile cause $r.SSE$			
Statistics	9.0448^{**}	5.7114^{*}	3.3601	7.9560^{**}	3.5698
Lags	[1]	[1]	[1]	[1]	[1]

Notes: Sup-Wald test statistics and the selected lag order (in square brackets) are reported. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

3. CONCLUDING REMARKS

We propose a two-step nonlinear quantile causality test approach to investigate the bidirectional relationship between oil price return and China's aggregate stock price return, and find that there are significant bidirectional causality correlations between the two in the low quantiles. The result is useful in prediction of oil and stock prices and risk management for policy makers, investors, risk managers and so force.

Our paper revisits the relationship between oil price return and aggregate stock price returns in China. It would be interesting to further assess their relationship in several other directions. One possible extension of this research is to further analyze whether there could be more prominent causal relationship in low quantiles between oil prices and stock prices in some industries especially in energy-sensitive industries.[6] The second direction is to distinguish the relationship between stock price return in China and oil price return fluctuation driven by supply-shock and demand-shock in the quantile causality framework.[7]

[6]Huang et al. (1996), Faff and Brailsford (1999), Hammoudeh et al. (2004), Hammoudeh et al. (2010), and Elyasiani et al. (2011) examine effect of oil prices changes on financial stock market at industrial level and find out more prominent positive effect of oil price changes in energy-sensitive industry.

[7]One noteworthy research done by Kilian (2009) categorizes oil price shocks into oil supply shock, oil market specific demand shock and shocks to the global demand for all industrial commodities and contends that each shock has different effect on the real price of oil and on US macroeconomic aggregates.

Appendix: Simulated Critical Values

	$\tau \in [0.05, 0.95]$			$\tau \in [0.05, 0.5]$			$\tau \in [0.5, 0.95]$			$\tau \in [0.05, 0.2]$			$\tau \in [0.2, 0.4]$			$\tau \in [0.4, 0.6]$		
	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%	10%	5%	1%
$p = 1$	7.997	9.584	13.072	6.88	8.342	12.097	6.802	8.336	11.867	5.86	7.31	10.592	5.273	6.666	10.409	5.032	6.455	9.999
$p = 2$	10.851	12.561	16.384	9.601	11.23	14.768	9.607	11.345	15.06	8.603	10.365	14.096	7.819	9.611	13.254	7.519	9.235	13.122
$p = 3$	13.325	14.933	19.045	12.046	13.904	17.879	11.93	13.803	17.989	10.751	12.576	16.616	9.97	11.836	15.835	9.517	11.303	15.22
$p = 4$	15.313	17.131	21.203	14.049	15.972	20.395	14.045	16.012	20.172	12.655	14.616	18.884	11.857	13.653	17.851	11.407	13.443	17.378
$p = 5$	17.351	19.309	23.486	15.943	17.954	22.53	15.848	17.874	22.257	14.4	16.423	20.664	13.471	15.517	19.815	13.194	15.275	19.528
$p = 6$	19.151	21.195	25.818	17.694	19.907	24.387	17.554	19.705	24.173	16.159	18.254	23.034	15.289	17.448	22.006	14.967	17.161	21.949
$p = 7$	21.045	23.142	27.887	19.514	21.658	26.205	19.422	21.616	26.133	17.875	20.128	24.834	16.983	19.159	23.831	16.556	18.744	23.491
$p = 8$	22.816	24.929	29.391	21.114	23.466	28.439	21.138	23.344	27.867	19.506	21.888	27.007	18.531	20.817	25.681	18.076	20.424	25.239
$p = 9$	24.364	26.558	31.173	22.777	25.064	29.912	22.674	24.869	29.778	21.055	23.472	28.577	20.038	22.468	27.425	19.545	22.052	27.261
$p = 10$	26.133	28.395	33.301	24.339	26.782	32.126	24.315	26.763	31.88	22.748	25.161	30.525	21.472	24.11	29.414	21.053	23.486	28.679

Note: We obtain the critical values by simulating the standard Brownian motion based on the Gaussian random walk with 3,000 i.i.d. $N(0,1)$ innovations. The simulation involves 20,000 replications. Note that $P\left\{\sup_{\tau\in[a,b]} \|\frac{B_p(\tau)}{\sqrt{\tau(1-\tau)}}\|^2 < c\right\} = P\left\{\sup_{s\in[a,b]} \|\frac{W_p(s)}{\sqrt{s}}\|^2 < c\right\}$, where W_p denotes a vector of p independent Brownian motions, and s_1 and s_2 are given by $a/(1-a)$ and $b/(1-b)$, respectively. David and Long (1981) and Andrews (1993) test and tabulate critical values for some values of s_2/s_1 and p.

REFERENCES

Andrews, Donald W. K., 1993. Test for parameter instability and structural change with unknown change point. *Econometrica* **61**, 821-856.

Broadstock, David C., and George Filis, 2014. Oil price shocks and stock market returns: New evidence from the United States and China. *Journal of International Financial Markets, Institutions and Money* **33**, 417-433.

Broadstock, David C., Hong Cao, and Dayong Zhang, 2012. Oil shocks and their impact on energy related stocks in China. *Energy Economics* **34**, 1888-1895.

Charles, Jones M., and Gautam Kaul, 1996. Oil and the stock markets. *Journal of Finance* **51**, 463-491.

Chen, Qian, and Xin Lv, 2015. The extreme-value dependence between the crude oil price and Chinese stock markets. *International Review of Economics & Finance* **39**, 121-132.

Chuang, Chia-Chang, Chung-Ming Kuan, and Hsin-Yi Lin, 2009. Causality in quantiles and dynamic stock return-volume relations. *Journal of Banking and Finance* **33**, 1351-1360.

Clive, Granger W. J., 1969. Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica* **37**, 424-438.

Cong, Rong-Gang, Yi-Ming Wei, Jian-Lin Jiao, and Ying Fan, 2008. Relationships between oil price shocks and stock market: An empirical analysis from China. *Energy Policy* **36**, 3544-3553.

Craig, Hiemstra, and Jonathan D. Jones, 1994. Testing for Linear and Nonlinear Granger Causality in the Stock Price-Volume Relation. *Journal of Finance* **49**, 1639-1664.

Denker, Manfred, and Gerhard Keller, 1983. On U-statistics and v. Mises' Statistics for weakly Dependent Processes. *Zeitschrift fÄur Wahrscheinlichkeitstheorie und verwandte Gebiete* **64**, 505-522.

Dickey, David A., and Wayne A. Fuller, 1981. Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica* **49**, 1057-1072.

Ding, Haoyuan, Terence Tai-leung Chong, and Sung Y. Park, 2014. Nonlinear dependence between stock and real estate markets in China. *Economics Letters* **124**, 526-529.

Ehung, Gi Baek, and William A. Brock, 1992. A general test for nonlinear Granger causality: Bivariate model. Working Paper, Iowa State University and University of Wisconsin at Madison.

Elyas, Elyasiani, Iqbal Mansur, and Babatunde Odusami, 2011. Oil Price Shocks and Industry Stock Returns. *Energy Economics* **33**, 966-974.

Erratum, David M., and DeLong, 1981. Crossing probabilities for a square root boundary by a bessel process. *Communications in Statistics-Theory and Methods* **10**, 2197-2213.

Evangelia, Papapetrou, 2001. Oil Price Shocks, Stock Market, Economic Activity and Employment in Greece. *Energy Economics* **23**, 511-532.

Faff, Robert W., and Timothy J. Brailsford, 1999. Oil Price Risk and the Australian Stock Market. *Journal of Energy Finance & Development* **4**, 69-87.

Fang, Chung-Rou, and Shih-Yi You, 2014. The impact of oil price shocks on the large emerging countries' stock prices: Evidence from China, India and Russia. *International Review of Economics and Finance* **29**, 330-338.

Filis, George, 2010. Macro economy, stock market and oil prices: do meaningful relationships exist among their cyclical fluctuations? *Energy Economics* **32**, 877-886.

Gilbert, Bassett, and Roger Koenker, 1982. An empirical quantile function for linear models with iid errors. *Journal of the American Statistical Association* **77**, 407-415.

Graham, Elliott, Thomas J. Rothenberg, and James H. Stock, 1996. Efficient tests for an autoregressive unit root. *Econometrica* **64**, 813-836.

Hamilton, James D., 1983. Oil and Macroeconomy since World War II. *Journal of Political Economy* **91**, 228-248.

Huang, Roger D., Ronald W. Masulis, and Hans R. Stoll, 1996. Energy shocks and financial markets. *Journal of Future Markets* **16**, 1-27.

Isaac, Miller J., Ronald A. Ratti, 2009. Crude oil and stock markets: stability, instability, and bubbles. *Energy Economics* **31**, 559-568.

Jungwook, Park, and Ronald A. Ratti, 2008. Oil price shocks and stock markets in the US and 13 European countries. *Energy Economics* **30**, 2587-2608.

Knut, Anton Mork, 1989. Oil and the macroeconomy when prices go up and down: an extension of Hamilton's results. *Journal of Political Economy* **97**, 740-744.

Kwiatkowski, Denis, Peter C.B. Phillips, Peter Schmidt, and Yongcheol Shin, 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics* **54**, 159-178.

Lutz, Kilian, 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *American Economic Review* **99**, 1053-1069.

Nicholas, Apergis, and Stephen M. Miller, 2009. Do structural oil-market shocks affect stock prices? *Energy Economics* **31**, 569-575.

Niels, Schulze, and Dirk G. Baur, 2005. Financial stability and extreme market conditions. SSRN Electronic Journal.

Perry, Sadorsky, 1999. Oil price shocks and stock market activity. *Energy Economics* **21**, 449-469.

Phillips, Peter, and Perron Pierre, 1988. Testing for a unit root in time series regression. *Biometrika* **75**, 335-346.

Roger, Koenker, and Gilbert Bassett, 1978. Regression quantiles. *Econometrcia* **46**, 33-50.

Roger, Koenker, and Jose A. F. Machado, 1999. Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association* **94**, 1296-1310.

Rumi, Masih, Sanjay Peters, and Lurion De Mello, 2011. Oil price volatility and stock price fluctuations in an emerging market: evidence from South Korea. *Energy Economics* **33**, 975-986.

Shawkat, Hammoudeh, Sel Dibooglu, and Eisa Aleisa, 2004. Relationships among US oil prices and oil industry equity indices. *International Review of Economics and Finance* **13**, 427-453.

Shawkat, Hammoudeh, Yuan Yuan, Thomas Chiang, and Mohan Nandha, 2010. Symmetric and asymmetric US sector return volatilities in presence of oil, financial and economic risks. *Energy Policy* **38**, 3922-3932.

Syed, Basher A., and Perry Sadorsky, 2006. Oil price risk and emerging stock markets. *Global Finance Journal* **17**, 224-251.