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Effect of Rare Disaster Risks on Crude Oil: Evidence from El Niño from Over 140 Years of Data

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Abstract

We extend the literature on the effect of rare disaster risks on commodities by examining the effect of the El Niño–Southern Oscillation (ENSO) on crude oil via the recently developed *k*-th order nonparametric causality-in-quantiles framework, utilizing a long range historical data set spanning the period 1876:01 to 2020:10. The methodology allows us to test for the predictive role of ENSO over the entire conditional distribution of not only real oil returns but also its volatility, by controlling for misspecification due to uncaptured nonlinearity and regime-changes. Empirical findings show that the Southern Oscillation Index (SOI), measuring the ENSO cycle, not only predicts real oil returns, but also volatility, over the entirety of the respective conditional distributions. The findings highlight the role of rare disaster risks over not only financial markets, but also commodities with significant implications for policymakers and investors.

Keywords: El Niño-Southern Oscillation; Real Oil Returns and Volatility; Higher-Order Nonparametric Causality in Quantiles Test

JEL Codes: C22, Q41, Q55

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1. Introduction

As outlined in Trenberth et al., (2007) the El Niño–Southern Oscillation (ENSO) is an irregularly periodic variation in winds and sea surface temperatures over the tropical eastern Pacific Ocean, affecting the climate of much of the tropics and subtropics. The warming phase of the sea temperature is known as El Niño and the cooling phase as La Niña. The two periods last several months each and typically occur every few years with varying intensity per period. The ENSO cycle changes the global climate pattern (Martin et al., 2013; Staupe-Delgado et al., 2018; Rojas et al., 2019), which in turn affects the demand and supply in the oil market, resulting in price fluctuations (Changnon, 1999; Cruz and Krausmann, 2013; Cashin et al., 2017; Qin et al., 2020). The literature suggests multiple channels in which ENSO can drive return and volatility dynamics in crude oil. From a demand perspective, the demand for oil could be affected by changes in global climate patterns due to the ENSO cycles, as warming weather patterns, in particular, negatively affect demand for energy commodities. Severe changes in the ecological environment can also force policy makers to implement policies to reduce energy consumption in order to reduce pollution that can be a driving factor behind the occurrence of natural disasters. Similarly, on the supply side, severe weather conditions can negatively affect the exploration, refining and transportation activities globally, thus opening a supply channel in which the ENSO cycle can affect oil market dynamics. Accordingly, one can establish a direct association between the ENSO cycles and crude oil price fluctuations from both demand and supply side related channels.

Considering that the ENSO cycle can cause severe natural disasters, such as droughts, floods and hurricanes (Cane, 2004; Alajo et al., 2006; Miyakawa et al., 2017; Hu and Fedorov, 2019), borrowing from the work of Demirer et al., (2018) on rare disaster risks and the oil market, we hypothesize that ENSO may also affect the volatility of the oil price. As pointed out by Demirer et al., (2018), this is likely to be the case because disaster risks contribute to jump risk in oil prices, and there is growing evidence suggesting that jumps account for a substantial part of the variation in crude oil prices, as well as a substantial part of the risk premium in oil derivatives prices (Asai et al., 2019, 2020). From yet another angle, several empirical studies have highlighted the role of rare disaster risks on first and second moment movements of asset (equities, bonds, currencies) prices (see for example, Berkmann et. al., 2011, 2017; Gupta et al., 2019a, 2019b; Gkillas et al., 2020), and given the well-known spillover effects between financial and oil markets (see for example, Tiwari et al., 2013, 2018; Balcilar et al., 2015,2017; Nazlioglu et al., 2020), there also exists an indirect channel through which rare disaster risks can affect returns and volatility of oil. Accordingly, the effect of time varying rare disaster risks on return and volatility dynamics in the oil market is supported both from an economic and empirical point of view.

Clearly, understanding the factors, and the role of the ENSO in this particular case, that drive oil market volatility, besides prices and/or returns, is a pertinent question both from the perspectives of policymakers and investors. From a policy making perspective, there is ample evidence that the first and second moment movements in crude oil may have an impact on inflation and predict recessions (Stock and Watson, 2003; Elder and Serletis, 2010; Plakandaras et al., 2017; van Eyden et al., 2019; Pierdzioch and Gupta, 2020). Particularly in emerging economies, energy imports contribute a great deal to persistent budget deficits and uncertainty in energy costs can present a significant challenge to policy makers in their economic growth projections. Moreover, the oil market's recent financialization has led to increased participation of hedge funds, pension funds and insurance companies in the market for commodities, thus rendering oil a profitable alternative investment in the portfolio decisions of financial institutions (Bahloul et al., 2018; Bonato 2019). Given that volatility, when interpreted as uncertainty, becomes a key input to investment decisions and portfolio choices (Poon and Granger, 2003), accurate estimates of oil-price volatility are of vital importance to oil traders.

Against this backdrop, to test our hypothesis that the ENSO cycle plays a predictive role over oil returns and volatility, we use the recently developed *k*-th order nonparametric causality-in-quantiles framework of Balcilar et al., (2018). The main novelties of this econometric framework and, thus, the empirical results of our paper are as follows: First, it is robust to misspecification errors, as it detects the underlying dependence structure between the examined dependent variable (i.e., real oil returns) vis-à-vis the regressor (i.e., the ENSO cycle represented by the Southern Oscillation Index, *SOI*). In our empirical exercise, we show that this is particularly important given that we find evidence of nonlinearity and regime changes between real oil returns and SOI, which supports the use of the nonparametric test. Second, this methodology allows not only causality-in-mean to be tested (i.e., the first moment), but also causality in the tails of the joint distribution of the variables. Our analysis reveals that this aspect is especially relevant in the light of the fact that the unconditional distribution of the dependent variable - i.e. real oil returns - tends to exhibit fat tails. Thus, the nonparametric causality-in-quantiles test captures predictability in bear, normal and bull market phases corresponding to the lower, median, and upper quantiles of the distribution. Third, we are able to investigate causality-in-variance and, thus, to study higher-order dependency. This again is highly pertinent since, during some periods, causality in the conditional-mean may not exist while, at the same time, higher-order predictability may turn out to be significant. Understandably, this framework which renders it possible to test for predictability over the entire conditional distributions of both real oil returns and volatility and simultaneously accounts for misspecification due to uncaptured nonlinearity and structural breaks, this framework is preferred to conditional mean-based nonparametric causality tests of Hiemstra and Jones (1994) and Diks and Panchenko (2005, 2006), and models of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-family.

To the best of our knowledge, this is the first paper that evaluates the predictive power of the ENSO cycle for real oil returns and volatility based on a nonparametric *k*-th order causality-in-quantiles framework. In addition to the novel econometric framework, we also utilize a unique monthly data set covering the period of 1876:01 to 2020:10, which basically involves the longest possible available history on these two variables of concern. The usage of about 145 years of data ensures that our analysis does not suffer from a sample selection bias. Our paper, thus, adds to the already existing large literature on the predictability of oil returns and volatility based on a wide array of linear and nonlinear models and macroeconomic, financial and behavioural predictors (see Gupta and Wohar (2017), Gkillas et al., (2020), Baumeister et al., (forthcoming), Salisu et al., (forthcoming) for detailed reviews in this regard), by considering the role of climate patterns. The remainder of the paper is organized as follows: Section 2 outlines the data and the methodology, while Section 3 discusses the econometric results, with Section 4 concluding the paper.

2. Data and Econometric Methodology

In this section, we present the data, and basics of the methodology for testing nonlinear causality via a hybrid approach as developed by Balcilar et al., (2018), which is based on the frameworks of Nishiyama et al., (2011) and Jeong et al., (2012).

2.1. Data

As far as the crude oil price is concerned, we use the monthly data of the nominal West Texas Intermediate (WTI) oil price, which is available from 1859, and is derived from the Global Financial Database.[1] The nominal value of the WTI oil price is deflated by the Consumer Price Index (CPI), obtained from the data segment of the website of Professor Robert J. Shiller,[2] with

[1] https://globalfinancialdata.com/.
[2] http://www.econ.yale.edu/~shiller/data.htm.

the data starting from January 1871. Naturally, the real oil price can only be computed from this date. We compute the log-returns of the real oil price (*ROILR*), by taking the first difference of the natural logarithms of the real oil price in percentages. For the metric to represent the ENSO cycle, we use the Southern Oscillation Index (*SOI*), obtained from the Bureau of Meteorology, Government of Australia.[3] The *SOI*, gives an indication of the development and intensity of El Niño or La Niña events in the Pacific Ocean. The *SOI* is calculated using the pressure differences between Tahiti and Darwin. Sustained negative (positive) values of the *SOI* below (above) −7 (+7) often indicate El Niño (La Niña) episodes. Low atmospheric pressure tends to occur over warm water and high pressure occurs over cold water, in part because of deep convection over the warm water. El Niño episodes are defined as sustained warming of the central and eastern tropical Pacific Ocean, and La Niña episodes are defined as sustained cooling of the central and eastern tropical Pacific Ocean, thus resulting in a decrease and an increase in the strength of the Pacific trade winds respectively. The *SOI* data is available from January, 1876, and hence our sample ranges between 1876:01-2020:10, i.e., 1738 observations, based on data availability of these two variables of concern at the time of writing this paper.[4] Figure 1 presents the time series plots for real oil returns (*ROILR*) and the Southern Oscillation Index (*SOI*) and Table 1 presents the summary statistics. *ROILR* and *SOI* are both negatively skewed and the excess kurtosis results in a non-normal distribution as indicated by the strong rejection of the null of normality under the Jarque-Bera test. The non-normality of the *ROILR* provides preliminary motivation to use a quantiles-based, rather than a conditional mean-based approach for our empirical analysis.

[INSERT TABLE 1]

[3] http://www.bom.gov.au/climate/current/soihtm1.shtml.

[4] The log-returns ensure that the oil data is mean-reverting, while the *SOI* is stationary in levels, which in turn meets the data requirements of the test employed. Understandably, we need to work with returns to analyze the impact on squared returns, i.e., volatility.

2.2. *Methodology*

Now turning to the k-th order nonparametric causality-in-quantiles test, let y_t denote *ROILR* and x_t the *SOI*.[5] Further, let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t| \bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability one. The (non)causality in the θ-th quantile hypotheses to be tested are:

$$H_0\colon\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \tag{1}$$

$$H_1\colon\ P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \tag{2}$$

Jeong et al., (2012) show that the feasible kernel-based test statistics has the following format:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{3}$$

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The *Nadarya-Watson* kernel estimator of $\hat{Q}_\theta(Y_{t-1})$ is given by

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{4}$$

with $L(\bullet)$ denoting the kernel function.

Balcilar et al., (2018) extend the framework of Jeong et al., (2012), based on Nishiyama et al., (2011), to the *second* (or higher) moment which allows us to test the causality between the *SOI* and *ROILR* volatility (*ROILRV*). In this case, the null and alternative hypotheses are given by:

[5] Our description of the technical details of the quantiles-based test is relatively compact and draws heavily on the expositions in Balcilar et al., (2020a, forthcoming).

$$H_0: \ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1, \quad k = 1,2,\dots,K \tag{5}$$

$$H_1: \ P\left\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1, \quad k = 1,2,\dots,K \tag{6}$$

The causality-in-variance test can then be calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. As pointed out by Balcilar et al., (2018) a rescaled version of the $\hat{J}_T$ has the standard normal distribution. Testing approach is sequential and failing to reject the test for $k = 1$ does not automatically lead to no-causality in the *second* moment; one can still construct the test for $k = 2$.

The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag-order of 2 based on the Schwarz Information Criterion (SIC). We determine h by the leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

3. Results

Before we discuss the findings from the k-th order causality-in-quantiles test, for the sake of completeness and comparability, we conduct the standard linear Granger causality test, with a lag-length of 2, as determined by the SIC. The resulting $\chi^2(2)$ statistic (with p-values in parenthesis) associated with the causality running from *SOI* to *ROILR* is found to be equal to 4.9074 (0.0860). Given these results, the null hypothesis, that *SOI* does not Granger cause *OILR*, cannot be rejected at the conventional 5% level of significance, though weak evidence of predictability is observed at the 10% level. Therefore, based on the standard linear test, we conclude that there is no evidence of statistically strong ENSO-related effects on real oil returns, in line with Qin et al., (2020), who too made similar observations using a wavelet-based approach.

Given the insignificant results obtained from the linear causality tests, we statistically examine the presence of nonlinearity and structural breaks in the relationship between *ROILR* and *SOI*. Nonlinearity and regime changes, if present, would motivate the use of the nonparametric k-th order quantiles-in-causality approach, as the quantiles-based test would be able to adequately capture nonlinearity and structural breaks in the link between the variables under investigation. For this purpose, we apply the Broock et al., (1996, BDS) test on the residuals from the *ROILR* equation involving 2 lags of *ROILR* and *SOI*. Table 2 presents the results of the BDS test of nonlinearity. We find strong evidence, at the highest level of significance, against the null hypothesis of *i.i.d.* residuals at various embedding dimensions (m), which, in turn, is indicative of nonlinearity in the relationship between *ROILR* and *SOI*. To further motivate the causality-in-quantiles approach, we next use the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to M structural breaks in the relationship between *ROILR* and *SOI*, allowing for heterogenous error distributions across the breaks. When we apply these tests again to the *ROILR* equation involving 2 lags of *ROILR* and *SOI*, we detect 5 breaks at: 1898:06, 1921:04, 1942:12, 1964:08, and 1986:04. The break dates are in line with the El Niño episodes.[6]

[INSERT TABLE 2]

In light of the strong evidence of nonlinearity and structural breaks in the link between *ROILR* and *SOI*, we now apply the causality-in-quantiles test, which is robust to misspecification due to its nonparametric (i.e., data-driven) approach, besides allowing us to test predictability for both oil returns and volatility. In Table 3, we present the results for the *higher-order* order causality-in-quantiles test for real oil returns (*ROILR*) and squared real oil returns, i.e., volatility (*ROILRV*), emanating from the *SOI* over the quantile range of 0.10 to 0.90. As can be seen, unlike the results discussed above derived from the linear framework, *SOI* is found to

[6] http://www.bom.gov.au/climate/enso/enlist/.

cause *ROILR* at the 1% level of significance over all the quantiles of the conditional distribution considered, with the strongest effects observed around the median to moderately high quantiles, i.e., 0.50 to 0.60. Understandably, this result originates from the ability of our approach to control for the presence of nonlinearity (as shown in Table 1) and regime changes via the usage of data-driven nonparametric functional forms defining the relationship between *ROILR* and *SOI*. As far as return volatility (*ROILRV*) is concerned, we draw a similar observation as for returns in that we find evidence of predictability over the entire conditional distribution, but now causality is strongest at the lower quantiles and tends to decline as we move to upper quantiles. Accordingly, our findings show that *SOI* causes both real oil returns and volatility, though the strength of predictability is asymmetric across the quantiles, with stronger causality around the median of returns, i.e., normal oil market conditions, and lower quantiles of volatility associated with low oil market risk.

[INSERT TABLE 3]

Examining the findings in Table 3, one interpretation of the relatively strong predictability of the ENSO cycle at the lower end of the conditional distribution of oil volatility is that it indicates the predictive role of disaster risks on return volatility is relatively greater during periods when the oil market is relatively calm. This suggests that the surprise factor related to disaster risks shows the greatest impact on oil market volatility during relatively calmer market states. From another perspective, stronger causality at lower volatility quantiles could be an indication that when volatility (risk) in this market is low, investors do not anticipate much of a reaction from the Federal Reserve in terms of interest rate decisions (Balcilar et al., 2020b). As a result, the rare disaster risk factor tends to play a bigger role compared to the high volatility periods, captured by the upper quantiles of squared returns, when investors expect a stronger monetary policy response to market conditions.

At the same time, relative weaker return predictability of the ENSO cycle around the extreme quantiles compared to the median quantiles, i.e. normal market states, could be an indication of herding in the oil market during extreme market states, thus rendering the informational content of the ENSO redundant for investors to predict the future path of oil returns. This line of reasoning is vindicated by the well-established leverage effect in the oil market (Kristoufek, 2014), which causes high and low oil returns to reduce volatility, and increase herding among oil traders (Brunetti et al., 2013). Indeed, examining the effect of the ENSO cycle on speculative activities in the oil market via the speculative ratio of Chan et al., (2015), we observe in Table 4 largely insignificant causal effects at the extreme quantiles of the speculative ratio.[7] Considering that extreme high (low) quantiles of the speculative ratio correspond to speculative (hedging) patterns by oil traders, the insignificant causal effect of the ENSO cycle during periods characterized by high level of speculation and hedging suggests that investors tend to ignore fundamental market information related to disaster risks and follow the market consensus via possible herding. Accordingly, such possible herding behavior renders the informational content of the ENSO cycle redundant during such periods, consistent with the relatively weaker return predictability of the ENSO cycle observed around the extreme return quantiles when investors are more likely to engage in herding.[8]

[INSERT TABLE 4]

4. Conclusion

The role of rare disaster risks on financial and commodity return dynamics is well established in the literature. Recently, studies have provided evidence, albeit weak, of the impact of the El Niño–Southern Oscillation (ENSO) cycle on oil price dynamics. Given this weak evidence, we

[7] The speculative ratio is measured as the trading volume divided by open interest for WTI futures traded on NYMEX (data obtained from Commodity Systems Inc.). Note that due to the availability of futures market data, the monthly speculative ratio series begins in 1983.

[8] Cakan et al., (2019) also establish a link between speculative behavior and herding in the global oil market associating greater speculation with herding behavior in major energy importer and exporter nations.

extend this sparse literature via the recently developed *k*-th order nonparametric causality-in-quantiles test of Balcilar et al., (2018), which in turn allows the predictive role of the ENSO over the entire conditional distribution of not only real oil returns (*ROILR*), but also its volatility (*ROILRV*), by controlling for misspecification due to uncaptured nonlinearity and regime-changes. Our results point out that the Southern Oscillation Index (*SOI*), capturing the ENSO cycle, not only predicts real oil returns, but also volatility, over the entirety of the respective conditional distributions, based on the longest span of historical monthly data associated with these two variables covering 1876:01 to 2020:10. These results highlight the predictive role of rare disaster risks over not only financial market volatility, but also commodity price fluctuations.

Our results can be used by policymakers to obtain information on the movements of the first- and second-moments of the oil market due to changes in climate patterns, and in the process, use this knowledge to anticipate economic activity, given that oil price movements may lead business cycles, and then accordingly make appropriate policy choices. Moreover, with volatility being a key input in portfolio decisions, the predictability of oil-market volatility due to the ENSO cycle is of vital importance to oil investors, as well as asymmetries in volatility patterns due to disaster related risks can be utilized to improve options pricing models.

Since in-sample predictability does not necessarily translate into out-of-sample gains, it is interesting to extend our analysis in future research to a full-fledged forecasting exercise using the *k*-th order nonparametric causality-in-quantiles method, as outlined in detail by Bonaccolto et al., (2018).

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Table 1. Summary Statistics.

Statistic	*ROILR*	*SOI*
Mean	0.0096	0.0494
Median	0.0000	0.2000
Maximum	54.5602	34.8000
Minimum	-56.1416	-42.6000
Std. Dev.	7.0333	10.4340
Skewness	-0.0549	-0.1817
Kurtosis	13.9347	3.2831
Jarque-Bera	8659.6370***	15.3688***
Observations	1738	

Note: *SOI* and *ROILR* are the Southern Oscillation Index and real oil returns, respectively. *** indicate rejection of the null hypothesis of normality at 1% level of significance.

Table 2. Brock *et al*. (1996, BDS) Test of Nonlinearity.

Independent	Dimension				
Variable	2	3	4	5	6
MDRI	14.0975***	17.2835***	19.6878***	22.0171***	24.8608***

Note: Entries correspond to the *z*-statistic of the BDS test for the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the real oil returns (*ROILR*) equation with 2 lags each of *ROILR* and the Southern Oscillation Index (*SOI*). * indicates rejection of the null hypothesis at 1% level of significance.

Table 3. *k*-th Order Causality-in-Quantiles Test Results.

Quantile	*ROILR*	*ROILRV*
0.10	3.3335^{***}	12.5992^{***}
0.20	4.8229^{***}	8.9996^{***}
0.30	5.0307^{***}	9.2491^{***}
0.40	4.7041^{***}	10.5854^{***}
0.50	11.0125^{***}	10.8090^{***}
0.60	13.1502^{***}	9.9403^{***}
0.70	6.6253^{***}	9.0746^{***}
0.80	3.8630^{***}	7.6191^{***}
0.90	2.7695^{***}	5.3934^{***}

Note: *** indicate rejection of the null hypothesis of no Granger causality at 1% level of significance (critical value of 2.575) from Southern Oscillation Index (*SOI*) to real oil returns (*ROILR*) and real oil return volatility (*ROILRV*) for a particular quantile.

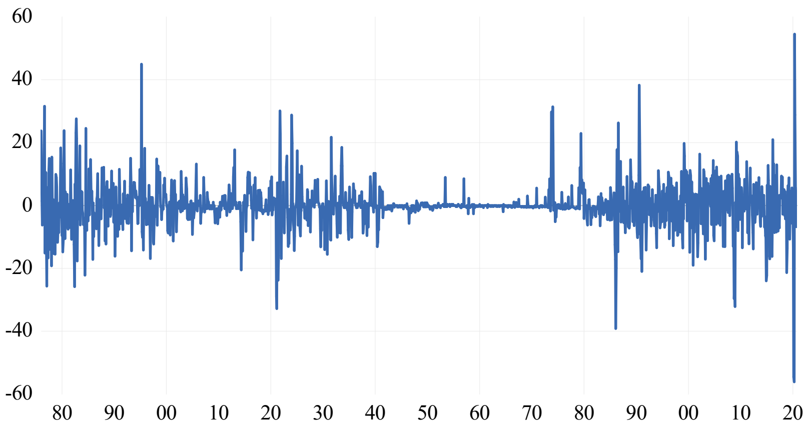
Table 4. *k*-th Order Causality-in-Quantiles Test Results for Speculative Activities.

Quantile	*SR*
0.10	1.5361
0.20	1.6246
0.30	2.2297**
0.40	3.2489***
0.50	3.0940***
0.60	3.2119***
0.70	3.0699***
0.80	1.8340*
0.90	1.5450

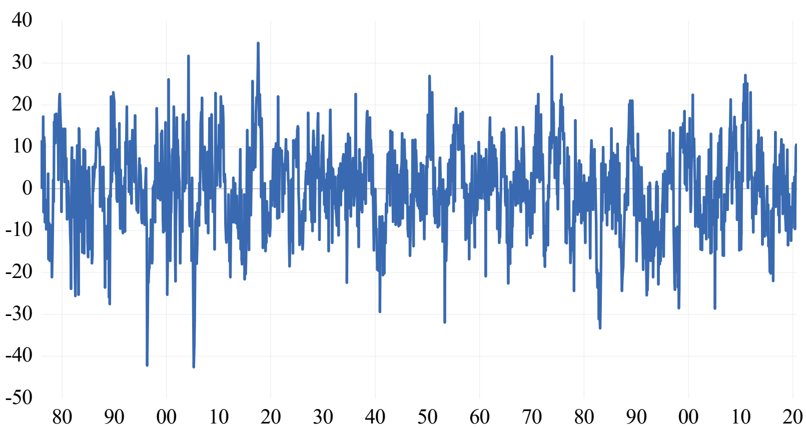
Note: ***, ** and * indicate rejection of the null hypothesis of no Granger causality at 1%, 5% and 10% levels of significance (critical values of 2.575, 1.96 and 1.645) respectively from Southern Oscillation Index (*SOI*) to monthly speculative ratios (*SR*) for WTI futures, traded on the NYMEX, for a particular quantile. *SR* is defined as trading volume divided by open interest.

Figure 1. Data Plots

1(a). Real Oil Return (*ROILR)*:



1(b). Southern Oscillation Index (*SOI)*:



Note: See Notes to Table 1.