Does Oil Predict Gold? A Nonparametric Causality-in-Quantiles Approach

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1 March 2017

Does Oil Predict Gold? A Nonparametric Causality-in-Quantiles Approach*

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Abstract

This paper examines the predictive power of oil price for gold price using the novel nonparametric causality-in-quantiles testing approach. The study uses weekly data over the April 1983-August 2016 period for both the spot and 1-month to 12-month futures markets. The new approach, the causality-in-quantile, allows one to test for causality-in-mean and causality-in-variance when there may be no causality in the first moment but higher order interdependencies may exist. The tests are preferred over the linear Granger causality test that might be subject to misleading results due to misspecification. Contrary to no predictability results obtained under misspecified linear structure, the nonparametric causality-in-quantiles test shows that oil price has a weak predictive power for the gold price. Moreover, the causality-in-variance tests obtain strong support for the predictive capacity of oil for gold market volatility. The results underline the importance of accounting for nonlinearity in the analysis of causality from oil to gold.

Keywords: Gold, Oil, Spot and futures markets; Quantile Causality.
JEL Codes: C22, G15

* We would like to thank an anonymous referee for helpful comments. However, any remaining errors are solely ours.

1. Introduction

On account of oil's frequent tradability, voluminous trades, high liquidity and synchronization of its movement, gold has held its righteous positions in not only national but in international economies as well. Oil is the commodity with the highest volume of trade and with higher price volatility and gold, on the other hand, is the most traded precious metal with the lowest price volatility. A comprehensive analysis of oil and gold prices suggests that prices of both are strongly related. Oil and gold hold a positive price correlation of 80% in the last 50 years.[1] There are a large number of studies suggesting that oil price changes give rise to price variations in gold. To illustrate, According to Sari et al. (2010) gold price changes are related to the oil price changes and oil price changes explain the 1.7% of the price change in gold. Hence, an empirical study is of enormous importance in examining this relationship and this study aims to examine the causality-in-quantiles running from oil to gold.

There are several channels accounting for the relation between oil and gold prices. Many oil-exporting countries, for instance, perform oil transaction in return for gold. Due to its nature of safe investment, oil revenues are invested in gold. Besides, the costs in gold mining are very much related to energy and oil issues. This being the case, a rise in energy and oil prices inevitably has an impact on the costs in gold mining. Another channel effective in explaining the relation between oil and gold prices is inflation. As a support to explain this connection, Narayan et al. (2010) argues that the relation between oil and gold prices can be best explained through inflation. Other things being equal, a rise in oil prices at the international scale will affect the prices in global terms and will have a negative effect on the oil importing countries, yielding a negative relation between oil and inflation. Nowadays, gold is regarded as an instrument investors buy to balance their portfolio during times with high inflation (Ghosh, 2011). Since gold is a safe means of investment (safe heaven) the price of gold goes up in high inflation periods, hence, as oil prices rise so does inflation and price of gold.

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[1] See Barisheff (2005).

The literature on oil and gold price relationship and their interaction with a specific emphasis on macroeconomic and financial issues is scant. Each economic crisis led to some studies into the issue, especially gold seen as a safe haven. One of the leading studies is that of Melvin and Sultan (1990) and Kim and Dilts (2011), in which they found out a high correlation between oil and gold in terms of export channel. Nevertheless, the literature hosts other studies with no evidence of the relationship between the rises in prices of oil and gold (e.g., Soytas et al. 2009; Liao and Chen, 2008; Sari et al. 2007; Hammoudeh and Yuan, 2008; Narayan et al. 2010; Simakova, 2011; Le and Chang, 2011a and Lee et al. 2012). Sari et al. (2007) examined the dynamic links among commodities such as the oil, gold, silver and copper and financial variables, exchange rate and the interest rate. Their result showed that gold and exchange rate have predictive power for the oil, but oil does not have significant explanatory power these commodities. Soytas et al. (2009) studied the dynamic relationships among the oil, commodities (gold and silver), and financial variables (dollar exchange rate and bond rate) in Turkey. They examined both the short- and long-run dynamic interactions and concluded that oil prices do not have significant explanatory power for the gold.

Thus, the empirical evidence on the relationship between the oil and gold markets can be best described as mixed, if not confusing. The studies on oil-gold relationship center more on whether oil has predictive power for gold and given the mixed evidence further studies are needed. The mixed evidence on the relationship between the oil and gold gets even more complicated due the use of different sample periods, methods and countries under consideration. What is more important is that no comprehensive and insightful study exists to date to examine the relationship between oil and gold prices. A study that takes into account of nonlinearities, structural breaks, outliers and effects of extreme markets conditions in the analysis of the oil and gold market relationship will resolve some of the ambiguities relating to the empirical studies.

Against this backdrop, the objective of the current study is to use the recently proposed nonparametric causality-in-quantiles test by of Balcilar et al. (2016a, b) to analyze the predictability of mean and variance of gold price by oil price. The weekly data for the spot and 1- to 12-month futures prices of oil and gold market have been employed. The sample period ends at 8/10/16 and the beginning of the sample varies from 4/6/83 to 1/8/86 due to the varying operation start-up times in the futures markets.

Our first contribution to the literature on oil and gold price is that, rather than focusing on specific episodes of market periods, we use a nonparametric quantile testing approach which is rich enough to consider all market conditions jointly (low volatility, high volatility, crises, crashes, or bubbles). Thus, we can examine the predictive content of the oil market for the gold market under different market conditions. This will allow us to see under what conditions oil does predict the gold or does not. Our second contribution to the literature is the consideration of the both spot and futures markets. To our knowledge Narayan et al. (2010) is the only study considering futures markets. However, our study considers dynamic nonparametric quantile Granger causality and, therefore, significantly differs from Narayan et al. (2010) which only considers contemporaneous relationship via a static regression. Our third contribution to the literature is the examination of causality not only in mean but also causality in variance (volatility). Previous literature only studied the predictive power of the oil for gold in mean. Oil market may have predictive power for the second moment (variance) even if it does not have predictive power for the first moment (mean). The predictive power of oil market for gold market volatility can even be more important for investors and portfolio manager in developing hedging strategies. Our last contribution to the literature on oil and gold price causal nexus is that we use a novel nonparametric causality-in-quantiles test recently proposed by Balcilar et al. (2016a, b) to study whether oil price causes gold price returns and volatility. Their test integrates the test for nonlinear causality of *k*-th order developed by Nishiyama et al. (2011) with the quantile-causality test advanced by Jeong et al. (2012) and, hence, can be considered to be a generalization of the former. The causality-in-quantiles approach mainly has three novel aspects: first, this approach identifies the dependence structure of the time series under consideration using a nonparametric estimation and therefore misspecification errors are at minimum level or none. Next, it is viable to test both causality-in-mean and causality-in-variance; this being the case, it allows for higher-order dependency investigation, considered an essential point since there might be no causality in the conditional-mean for some periods, but higher-order dependency might be exists in the same periods. Finally, to date, this paper is the first one to examine the predictability and volatility of gold returns with the nonparametric causality-in-quantiles method, to the best knowledge of the authors. Our results show that oil prices have a weak predictive power for gold markets, as suggested by the results of the nonparametric causality tests. Still, we obtain strong evidence for causality-in-variance tests as we strongly reject the null hypothesis that oil prices does not *Granger* cause gold price volatility for spot and the futures markets at all maturities.

The paper is organized as the following: Section-2 accommodates the literature review, Section-3 introduces the method and Section-4 presents the data and the results and lastly Section-5 presents the conclusion.

2. Literature Review

There are some studies (e.g., Zhang and Wei, 2010) holding that oil and gold prices have high correlation, which is attributed to the phenomenon that high oil prices could have negative effect for economies and which in turn has an adverse effect that lowers the share prices (Kilian, 2009). Also, according to Melvin and Sultan (1990), export revenue channel may be used to explain the relationship between oil and gold prices. In an attempt to distribute the risks involved and to sustain the value of commodities and in order to possess more gold in their portfolio, major oil exporting countries invest the revenues obtained from oil in gold, paving the way for a rise in price of gold by increasing the demand. Finally, as stated by Narayan et al. (2010), Hooker (2002), Hunt (2006) and Beckmann and Czudaj (2013), inflation channel fits well in explaining the relation between oil and gold markets. On the other hand, there are studies, e.g., Le and Chang (2012), Bampinas and Panagiotidis (2015), claiming that oil and gold prices go hand in hand due to the correlation stemming from the volatility in US dollars and in international politics.

From the empirical perspectives, there are studies using time series data for a given country (Abhyankar et al. 2013; Mollick and Assefa, 2013; Reboredo, 2013; Wang and Chueh, 2013; Tiwari and Sahadudheen, 2015; and Ghosh and Kanjilal, 2016) and studies with cross-national data (Cunado and Perez de Gracia, 2003; Cunado and Perez de Gracia, 2005; Cologni and Manera, 2008; Asteriou and Bashmakova, 2013; Wang et al. 2013; Degiannakis et al. 2014; and Cunado and de Gracia, 2014). Considering the energy sectors, studies with the theme of oil and stock markets are on the increase (e.g. Basher and Sadorsky, 2006; Park and Ratti, 2008; Kilian and Park, 2009; and Broadstock and Filis, 2014). As suggested by Kilian and Park (2009), the reaction of real stock returns depends on the demand-driven increases or supply shock in the crude oil market.

A position of a country in the global crude oil market is very much related to the impacts of oil price uncertainty, as shown by Wang et al. (2013). They reveal that, compared to oil-importing countries, the relation between demand uncertainties on stock market is negative, much stronger and more persistent in oil exporting countries. Furthermore, there are studies incorporating short-term interest rates in their models to determine the effect of oil price shock on stock markets (e.g., Cong et al. 2008 and Park and Ratti, 2008).

Exchange rate is another variable used in examining the stock market revenues (Mishra, 2004). However, the results obtained from studies using exchange rates could yield misleading results because they do not integrate oil prices as an important variable, a significant one in the relation between exchange rate and stock market (Abdelaziz et al. 2008).

What is more, the number of studies on the relations between gold prices and macroeconomic variables is fewer when compared with oil prices (Patel, 2013; Reboredo and Rivera-Castro 2014; Arouri et al. 2015; Beckmann et al. 2015; and Pierdzioch et al. 2015). The theoretical framework puts forward that the volatility in the exchange rate of dollar have an impact on gold prices, for gold price is quoted in US dollars. The price of gold is likely to go up in the event of dollar depreciation and the value of gold is sustained in this manner. For this reason, gold is seen as a safe asset against currency fluctuations, especially for investors with assets in dollars. Capie et al. (2005), Sjaastad (2008), Reboredo and Rivera-Castro (2014) and Beckmann et al. (2015) are among those who examined the relation between gold price and exchange rate empirically. Zhang and Wei (2010) examined the long-run relationship between oil and gold markets and concluded that these markets are cointegrated. They also found a one-way linear Granger causality from the oil market to the gold market and obtain evidence that causality in not nonlinear using Hiemstra and Jones (1994) nonlinear Granger causality test. Compared to Zhang and Wei (2010), our study finds nonlinear Granger causality evidence in the mid-quantile ranges (generally from 0.20th 0.70th quantiles). We also consider causality in variance (2nd moment) not only in the mean (1st moment). Tiwari and Sahadudheen (2015) used univariate GARCH in mean models to examine the impact of the oil prices on the gold. Their findings showed a positive significant effect of oil on the gold. Our study is quite different than Tiwari and Sahadudheen (2015) as they use a parametric GARCH in mean model with linear conditional mean specification. Our study performs a nonparametric causality-in-quantiles tests for 2nd order causality while Tiwari and Sahadudheen (2015) only considers a GARCH error specification and they do not test for causality in variance. In addition, the literature on the relation between such strategic commodities as oil and gold and macro-financial variables within a multivariate context is limited, on the whole (see, Christiano et al. 1996; Awokuse and Yang, 2003; Sari et al. 2010; Bhunia, 2013; Chang et al. 2013; and Hussin et al. 2013).

3. Methodology

By building on the framework of Nishiyama et al. (2011) and Jeong et al. (2012) we use a novel methodology as advanced by Balcilar et al. (2016a, b), a method that is useful in detecting nonlinear causality through a hybrid approach. The returns on gold is designated as y_t while the oil return is designated as x_t. Based on Jeong et al. (2012), we define the quantile-based causality as follow[2]: x_t does not cause y_t in the θ-quantile with regards to the lag-vector of $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

$$Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) = Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}) \quad (1)$$

x_t is presumably cause of y_t in the θ-th quantile with regards to $\{y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}\}$ if

$$Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p}) \neq Q_\theta(y_t|y_{t-1}, \dots, y_{t-p}) \quad (2)$$

Here, $Q_\theta(y_t|\cdot)$ is the θ-th quantile of y_t. The conditional quantiles of y_t, $Q_\theta(y_t|\cdot)$, depends on *t* and the quantiles are restricted between zero and one, i.e., $0 < \theta < 1$.

For a compact presentation of the causality-in-quantiles tests, we define the following vectors $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, and $Z_t = (X_t, Y_t)$. L*et al*so define the conditional distribution functions $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t|Y_{t-1})$, which signify the distribution functions of y_t conditioned on vectors Z_{t-1} and Y_{t-1}, respectively. Moreover, the conditional distribution $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ is presumed to be completely continuous in y_t for nearly all Z_{t-1}. By 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 can see that $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$, which holds with a probability equal to one. As a result, the hypotheses to be evaluated for the causality-in-quantiles based on equations (1) and (2) can be represented as:

$$H_0: \; P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \quad (3)$$

$$H_1: \; P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \quad (4)$$

[2] The exposition in this section closely follows Nishiyama *et al.,* (2011) and Jeong *et al.,* (2012).

In order to define a measurable metric for the practical implementation of the causality-in-quantiles tests, Jeong et al. (2012) make use of the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t\text{-}1}) f_Z(Z_{t\text{-}1})\}$, where ε_t denotes the regression error and $f_Z(Z_{t\text{-}1})$ denotes the marginal density function of Z_{t-1}. Consequently, the causality-in-quantiles test is based on the regression error ε_t. The regression error ε_t arises based on the null hypothesis specified in equation (3), which would be true, if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t\text{-}1})|Z_{t\text{-}1}\}] = \theta$. In order to make the regression error explicit, we rewrite this last statement as $\mathbf{1}\{y_t \leq Q_\theta(Y_{t\text{-}1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Now, following Jeong et al. (2012), based on the regression error, the distance metric can be defined as:

$$J = E\left[\left\{F_{y_t|Z_{t\text{-}1}}\{Q_\theta(Y_{t\text{-}1})|Z_{t\text{-}1}\}\text{-}\theta\right\}^2 f_Z(Z_{t\text{-}1})\right] \tag{5}$$

In relation to equations (3) and (4), it is crucial to understand that $J \geq 0$. The statement will hold with an equality, i.e., $J = 0$, if and only if the null H_0 in equation (3) is true, while $J > 0$ holds under the alternative H_1 in equation (4). The feasible counterpart of the distance measure J in equation (5) gives us a kernel-based causality-in-quantiles test statistics for the fixed quantile θ and defined as:

$$\hat{J}_T = \frac{1}{T(T\text{-}1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t\text{-}1}\text{-}Z_{s\text{-}1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{6}$$

where $K(\cdot)$ denotes a known kernel function, h is the bandwidth for the kernel estimation, T denotes the sample size, and p represents the lag-order used for defining vector Z_t. Jeong *et al*. (2012) establish that the re-scaled statistics $Th^p\hat{J}_T/\hat{\sigma}_0$ is asymptotically distributed as standard normal, where $\hat{\sigma}_0 = \sqrt{2}\theta(1-\theta)\sqrt{1/(T(T-1)h^{2p})}\sqrt{\sum_{t\neq s} K^2((Z_{t-1}\text{-}Z_{s-1})/h)}$. The most crucial element of the test statistics $\hat{J}_T$ is the regression error $\hat{\varepsilon}_t$. In our particular case, the estimator of the unknown regression error is defined as:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t\text{-}1})\}\text{-}\theta \tag{7}$$

In equation (7), the quantile estimator $\hat{Q}_\theta(Y_{t\text{-}1})$ yields an estimate of the θ-th conditional quantile of y_t given Y_{t-1}. We estimate $\hat{Q}_\theta(Y_{t\text{-}1})$ by employing the nonparametric kernel approach as:

$$\hat{Q}_\theta(Y_{t\text{-}1}) = \hat{F}^{\text{-}1}_{y_t|Y_{t\text{-}1}}(\theta|Y_{t\text{-}1}) \tag{8}$$

where $\hat{F}_{y_t|Y_{t\text{-}1}}(y_t|Y_{t\text{-}1})$ denote the *Nadarya-Watson* kernel estimator given by:

$$\hat{F}_{y_t|Y_{t\text{-}1}}(y_t|Y_{t\text{-}1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t\text{-}1}\text{-}Y_{s\text{-}1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{Y_{t\text{-}1}\text{-}Y_{s\text{-}1}}{h}\right)} \tag{9}$$

with $L(\cdot)$ denote a known kernel function and h is the bandwidth used in the kernel estimation.

The causality in variance implies volatility transmission, which may exist even there is no causality in the mean (1st moment). Testing for Granger causality in the second or higher moments has some complications and the procedure for such tests should be carefully defined since rejection of causality in the moment m does not imply non-causality in the moment k for $m < k$. We begin by employing Nishiyama et al. (2011) nonparametric Granger quantile causality method. In order to demonstrate the causality in higher order moments, first we examine the process below for y_t:

$$y_t = g(Y_{t\text{-}1}) + \sigma(X_{t\text{-}1})\varepsilon_t \tag{10}$$

where ε_t denote an independently and identically distributed (*iid*) process; the unknown functions $\sigma(\cdot)$ and $g(\cdot)$ satisfy some properties that are sufficient for the stationarity of y_t. Although, this representation does not permit linear or non-linear causalities from $X_{t\text{-}1}$ to y_t, it does allow $X_{t\text{-}1}$ to have predictive content for y_t^2 when $\sigma(\cdot)$ is an established nonlinear function. The representation in equation (10) illustrates that squares for X_{t-1} does not necessarily enter into the nonlinear function $\sigma(\cdot)$. Thus, we re-specify equations (3) and (4) into a null H_0 and alternative H_1 hypothesis for causality in variance as follows:

$$H_0\text{:}\ \ P\left\{F_{y_t^2|Z_{t\text{-}1}}\{Q_\theta(Y_{t\text{-}1})|Z_{t\text{-}1}\} = \theta\right\} = 1 \tag{11}$$

$$H_1\text{:}\ \ P\left\{F_{y_t^2|Z_{t\text{-}1}}\{Q_\theta(Y_{t\text{-}1})|Z_{t\text{-}1}\} = \theta\right\} < 1 \tag{12}$$

In order to get a feasible test statistic for testing the null hypothesis H_0 in equation (11), we substitute y_t in equations (6) to (9) with y_t^2. A problem may arise with the causality test based on the definition given in equation (10), since there may be causality in the second moment (variance) along with the causality in the conditional first moment (mean). We can illustrate this with the following model:

$$y_t = g(X_{t\text{-}1}, Y_{t\text{-}1}) + \varepsilon_t \tag{13}$$

Therefore, the higher order causality-in-quantiles can be stated as:

$$H_0\text{:}\ \ P\left\{F_{y_t^k|Z_{t\text{-}1}}\{Q_\theta(Y_{t\text{-}1})|Z_{t\text{-}1}\} = \theta\right\} = 1 \quad \text{for } k = 1,2,\dots,K \tag{14}$$

$$H_1\text{:}\ \ P\left\{F_{y_t^k|Z_{t\text{-}1}}\{Q_\theta(Y_{t\text{-}1})|Z_{t\text{-}1}\} = \theta\right\} < 1 \quad \text{for } k = 1,2,\dots,K \tag{15}$$

Incorporating the whole concept, we specify that x_t Granger causes y_t in quantile θ up to K-th moment using equation (14) to formulate the test statistic of equation (6) for each k. Nishiyama et al. (2011) construct nonparametric Granger causality tests using the density-weighted approach as in Jeong et al. (2011) and show that density-weighted nonparametric tests in higher moments have the same asymptotic normal distribution as the test for causality in first moment, although some stronger moment conditions might be necessary. Nevertheless, it is not an easy task to test for all $k = 1,2, \dots, K$ jointly, since the statistics are jointly correlated (Nishiyama et al. 2011). In order to systematically overcome this issue, we follow the sequential testing approach in Nishiyama et al. (2011) to test for causality in both models defined in equations (10) and (13). In this approach, we first test for nonparametric Granger causality in the first moment ($k = 1$), but still continue for testing causality in variance even if the non-causality is not rejected. That is, if the null for $k = 1$ is not rejected, then there might still be causality in the second moment and, thus, we construct the tests for $k = 2$. This approach allows us to test the existence of causality only in variance as well as the causality in the mean and variance successively. Conclusively, we can investigate the existence of causality-in-mean and causality-in-variance sequentially. The empirical application of causality testing through quantiles require identifying three crucial choices: the lag order p, the bandwidth h, and the kernel type for $K(\cdot)$ and $L(\cdot)$ in equations (6) and (9), respectively. In this study, we make use of lag order of 7 based on the Schwarz Information Criterion (SIC) under a VAR involving oil returns and gold returns. Moreover, when it comes to choosing lags, the SIC is considered being parsimonious compared to other lag-length selection criteria. The SIC helps overcome the issue of over-parametrization usually arising with nonparametric frameworks.[3] The bandwidth value is chosen by employing the least squares cross-validation techniques.[4] Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

4. Data and Empirical Findings

4.1 Data

We employ weekly US dollar closing prices of crude oil spot and futures contracts traded on the New York Mercantile Exchange as well as weekly US dollar prices of gold spot and

[3] Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an over-parameterized model, while the SIC is asymptotically consistent.

[4] For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

futures contract on London Bullion Market (LBMA). All data is sourced from Datastream. The data used for futures prices of oil and gold is for 1-month to 12-month maturities. The data span used in this paper differs for both markets, for gold and oil markets started due to their operations starting on different dates. The oil and gold series in the sample is presented in the first column of Table 1. The data span is until 08/10/2016 and beginning of the sample is given in the last column of Table 1. Figure 1 displays the time series plots all series.

Degrees of sensitivity of gold markets to oil prices tend to change in different markets, as shown by the empirical evidence. To illustrate, while oil price rises are to the benefit of oil exporting countries, it is not the same for oil importing countries. Market price (such as Gold) would usually have an averaging affect across market and might not uncover the causal links in oil and gold prices. Since it is our objective to describe a dependence structure, we found it to be more appropriate to use weekly data in this paper. The use of daily data could mask the dependence structure we wished to examine due to the probable effects of drifts, noise, non-stationary variances, long memory or sudden jumps which could disrupt the modelling of marginal distributions. In addition, due to the highly volatile structure of oil and gold markets, it would be nearly impossible to grasp the relation between oil and gold prices, which is why we use weekly data. As indicated by standard unit root tests, oil and gold series are non-stationary in log-levels[5]. The nonparametric causality-in-quantile test requires stationary data and for this reason, we use the first-differences of the natural logarithmic values of the oil and gold price in percentage.

 # Insert Figure 1 in Here #

Key points of the data series under consideration are presented in Table 1, which reports the mean, standard deviation, Kurtosis, Skewness, the Jarque-Bera normality test (JB), the Ljung-Box first [$Q(1)$] and the fifth [$Q(5)$] autocorrelation tests, and the first [ARCH(1)] and the fifth [ARCH(5)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH) for oil and gold spot and futures contracts. The mean of oil market returns is at its lowest for futures price but as for the spot prices there is a gradual increase with the longest maturity of 12-month contracts with highest average price of 0.32. On the other hand, as for the mean of gold market returns, it is at its lowest with

[5] Complete details of the unit root tests are available upon request from the authors.

maturity of 12-month contract for futures price but there is a gradual increase for spot prices, with the lowest maturity of 1-months contract with the highest average price of 0.68. In terms of volatility, oil market returns exhibit a more volatile structure than gold market returns. Based on the negative values of the skewness, there is a higher possibility of large decreases in returns, with one exception. The exception is that, considering oil market returns, the 12-month contract returns has a positive skewness estimate around 0.89. Based on the kurtosis statistic, we observe fat-tailed distribution for all return series. As a more important finding, the variables under consideration are skewed to left, with positive excess kurtosis, leading to non-normal distributions, as shown by the strong rejection of Jarque-Bera statistic at 1% significance level. The use of the causality-in-quantiles test is first justified by the fat-tailed distributions of both returns. We observe significant serial correlation for oil market returns, while significant serial correlation is not found for gold market returns, as suggested by Ljung-Box statistic. There are ARCH (autoregressive conditional heteroscedasticity) effects in all the return series, as shown by the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) statistic.

 # Insert Table 1 in Here #

As well as examining the causality-in-quantiles from oil to gold, for completeness and comparability, we also conducted the standard linear Granger causality test based on a linear vector autoregression (VAR) model. Table 2 reports the results of linear Granger causality tests. All of the F-statistics reported in Table 2 for the null hypothesis that oil returns does not Granger cause gold returns are less than 1.8. Hence, we can conclude that even at significance levels greater than 10%, there is no support of predictability running from oil to gold in a linear VAR framework.

 # Insert Table 2 in Here #

Subsequently, using the nonparametric quantile-in-causality approach, a nonparametric (i.e., data-driven) approach, we examine the possibility of nonlinear dependence between the oil returns and gold returns. In order to serve this purpose, Brock et al. (1996, BDS) test is implemented on the residuals of an VAR(1) model for both returns. We apply the BDS test to the residuals of oil returns and gold returns equation in the VAR(1) model. As Table 3 shows, we reject the null of *i.i.d.* residuals at various embedding dimensions (*m*), since there is strong evidence at the highest level of significance against linearity. Based on this result, we conclude that there is strong evidence of nonlinearity in oil returns and gold returns. This means that Granger causality tests in a linear framework might lead to unreliable results due to misspecification errors. Because of the strong evidence of nonlinearity, we implement the causality-in-quantiles test, which is deemed robust against, jumps, outliers, structural breaks, and nonlinear dependence.

 # Insert Table 3 in Here #

Given the strong evidence of nonlinearity obtained from the BDS tests, we further investigate whether nonlinear Granger causality running from oil markets to gold markets exists. In order to test for full sample nonlinear Granger causality, we use the nonlinear Granger causality test of Diks and Panchenko (2006).[6] Diks and Panchenko (2006) nonlinear Granger causality test results are presented in Table 4. We perform the tests for embedding dimension $m = 2, 3, 4$ in order be robust against the lag order used in the test. The tests results reported in Table 4 show that null hypothesis of no full sample nonlinear Granger causality running from the oil to gold is rejected for none of the spot and futures markets. This results holds unanimously for all embedding dimensions considered. Given the nonexistence of any evidence on the full sample nonlinear Granger causality, we next turn to nonparametric causality-in-quantiles tests, which considers all quantiles of the distribution not only the center of the distribution.

 # Insert Table 4 in Here #

The results of the quantile causality in mean and variance from the oil market series to the gold market series are presented in Figure 2. The horizontal axis shows the quantiles and the vertical axis shows the nonparametric causality test statistics corresponding to the quantile in the horizontal axis. While 5% critical value is 1.96, 10 percent critical value is 1.64. Horizontal thin solid lines show the critical value of 5% and thin two-dashed lines represent 10% critical values. There is clear difference between the quantile causality in mean and quantile causality in variance analysis, as shown by the results in Figure 2. According to the quantile causality test in mean the null hypothesis that oil does not *Granger* cause gold is not

[6] Diks and Panchenko (2006) test corrects the over-rejection problem observed in Hiemstra and Jones (1994) test.

rejected ($p > 0.05$) with a critical value of 1.96 over the quantile range of 0.25 to 0.60. The only exception occurs at the quantile of 0.55. Except for one or two quantiles, the causality-in-quantile test does reject the null hypothesis ($p > 0.05$) within the quantile range of 0.10 to 0.90 for future markets with differing maturities (1-month, 2-month, 3-month, 4-month, 6-month, 9-month). On the other hand, the null hypothesis that oil does not *Granger* cause gold is rejected ($p < 0.05$) over the quantile range of 0.45 to 0.70 for futures market at 5-month maturity as well as the quantile range of 0.25 to 0.65 for futures markets at 10-month and 11-month maturities, and the quantile range of 0.25 to 0.75 for futures market at 12-month maturity. The quantile causality test in mean for the spot and futures markets at 5-month, 10-month, 11-month, and 12-month maturities exhibits that oil returns has predictive power on gold returns. Yet, as for maturities of 1-month, 2-month, 3-month, 4-month, 6-month, 9-month, there is week evidence that oil returns have predictive power for gold returns for the futures markets. For these maturities, oil has predictive power for gold only around the quantiles from 0.40 to 0.60 and the null is rejected only at 10% level for the 3-month maturity. In sum, oil returns have no predictive power for gold returns in bearish (lower quantiles) and bullish (upper quantiles) market conditions.

According to the quantile causality in variance test results shown in Figure 2, the null hypothesis that oil does not *Granger* cause gold in variance (2nd moment) is rejected ($p < 0.05$) over the quantile range of about from 0.15 to 0.75 for all spot and all futures markets. This result shows that oil spot and all oil futures have strong predictive content for spot and all future price volatility (variance) of gold market. Hence, there is no evidence supporting the predictive power of oil for gold returns in the linear model. However, because of the nonlinearity, the result of linear Granger causality is misleading. This in mind, nonparametric causality-in-quantiles test results indicate that spot and future prices of oil have predictive content for spot and future gold price volatility. This, in part, suggests that contrary to equities, oil market moves in connection with gold market volatility during the periods of stress.

The reason for this could be can be explained by the fact that crude oil is an essential raw material in industrial manufacturing. Thus, global economic growth is much more linked with crude oil than gold. For this reason, investors consider price changes in crude oil an important phenomenon. With respect to global industrialization and globalization of markets, crude oil futures impact other futures available, for it is the largest commodity futures in the world. The rapid development in alternative energy resources made it possible for the USA to incorporate corn and white sugar in bioethanol in order to produce biodiesel fuel and this is an example of the close link between crude oil prices and grease products, soybean and corns. In summary, due to the extensive use of crude oil in the world global markets, the commodity prices in world markets on the whole rest with the fluctuations of crude oil prices.

 # Insert Figure 2 in Here #

The results in Figure 2 shows that the strength of the evidence of causality from oil market to gold market, both in mean and variance, exhibits a hump-shaped pattern across quantiles. Similar observations can be made across all the spot and 1- to 12-month maturities. The hump-shaped pattern of causality is a new finding in this study and illustrates an advantage of using our nonparametric causality-in-quantiles tests: A researcher who only studies the median of the conditional distribution of gold returns and/or gold volatility would likely to find strong evidence of predictive power from the oil to the gold, but, at the same time, would completely miss that this evidence substantially weakens when the quantiles that are farther away from the median are considered. We further point out that hump-shaped curves in Figure 2 are asymmetric, where noncausality part is longer on the right tail and the curves decline smoother on the right half of the figures. This implies that evidence of noncausality is weaker on the right tail (extreme gold price increases) compared to the left tail (extreme gold price decreases).

5. Conclusion

The extant literature so far has examined the oil market with respect to its predictive power for gold markets. This paper adds to this literature by means of examining the predictability of gold markets for the mean and volatility by the oil market. To serve this purpose, using weekly data, standard linear Granger causality test is implemented but no evidence has been found about causality running from oil market to gold market. Following the nonlinearity tests, we find oil returns relationship with gold returns have nonlinear characteristics, which suggests that the linear causality tests suffer from misspecification, thus yielding unreliable results. In order to overcome this problem, we employ a nonparametric causality-in-quantiles test, incorporating the test for nonlinear causality of k-th order developed by Nishiyama et al. (2011) with the causality-in-quantiles test developed by Jeong et al. (2012). This approach, the causality-in-quantiles, enables us to examine causality-in-mean as well as the causality in variance. In this way, even when there might be no causality in mean, we can still examine the causality-in-variance (volatility). The nonparametric causality tests in mean indicate that oil prices have a weak predictive content for gold market. Yet, the null hypothesis that oil prices does not *Granger* cause gold price volatility for spot and the futures markets at all maturities is strongly rejected for both spot and futures markets. The results on the nexus between oil market and gold market, on the whole, underline the significance of detecting and modeling nonlinearity when examining predictability via causal relationships.

The hump-shaped pattern in causality-in-quantiles tests we have found for causality running from oil markets to gold markets, both for causality in mean and variance, highlights the strong causal effects at the center of the conditional distribution of gold-price fluctuations. In other words, the strongest effects of oil returns on gold returns and gold volatility may occur on average, especially at higher data-frequencies (weekly data), in times of normal rather than in times of exceptional movements of the gold price. However, this finding does not rule out that singular events like the outbreak of a financial crisis or geopolitical turbulences that trigger significant movements of the gold price, but it rather highlights that investors and policymakers should study the entire conditional distribution of gold-price movements when looking for causal effects of oil that operate, for example, in normal times and in times of gold market turmoil. Similarly, an asymmetric hump-shaped pattern of causality highlights that the strength of causality effects differs across the upper and lower parts of the conditional distribution of gold-price movements.

As we pointed out, events such as important financial crisis or geopolitical events that trigger significant gold price fluctuations are not ruled out by the strong causality evidence on the center of the gold returns distribution, but it rather highlights that investors and policymakers when looking for causal effects from oil to gold markets should consider the entire conditional distribution of gold-price movements, not only the center of the distribution which corresponds to low return periods. The asymmetric hump-shaped pattern of causality running from oil to gold markets found in our study highlights that the strength of causality effects differs across the upper and lower parts of the conditional distribution of gold price movements. These results imply that investors should be aware that predictive power of oil prices for the gold prices observed in normal times weakens during extreme market conditions (low and high gold price periods). In terms of hedging strategies for portfolio managers, our results show that gold is a safe haven against extreme oil price movements, but it not an effective hedge instrument against oil price during the normal market periods. Investors should also know that oil precise would only indicate direction of gold price movements during normal market periods, oil prices do fail to predict the extreme gold price movements, particularly the extreme price increases.

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Table 1. Descriptive statistics for returns (%)

	n	Mean	S.D.	Min	Max	Skewness	Kurtosis	JB	Q(1)	Q(5)	ARCH(1)	ARCH(4)	Starting Period
						Panel A: Oil market returns							
Spot	1596	0.030	5.200	-29.255	30.305	-0.153	2.942	584.547***	6.104**	23.318***	83.207***	149.479***	1/8/86
1-month	1741	0.020	4.881	-37.288	24.390	-0.310	4.309	1379.907***	5.189**	23.360***	58.484***	114.767***	4/6/83
2-month	1741	0.021	4.482	-36.534	23.980	-0.370	4.814	1726.989***	3.493*	21.033***	52.602***	82.984***	4/6/83
3-month	1741	0.022	4.210	-32.128	23.298	-0.365	4.416	1458.796***	3.350*	20.126***	49.219***	86.112***	4/6/83
4-month	1741	0.024	4.000	-28.831	22.478	-0.344	4.165	1297.596***	3.624*	20.126***	52.244***	95.926***	4/6/83
5-month	1741	0.025	3.865	-25.995	21.700	-0.255	4.222	1317.403***	5.213**	21.647***	65.326***	113.488***	4/6/83
6-month	1741	0.026	3.696	-23.377	21.120	-0.298	3.843	1101.367***	4.278**	21.304***	62.175***	117.932***	4/6/83
7-month	1741	0.027	3.579	-20.875	20.675	-0.247	3.649	987.705***	4.600**	20.206***	70.764***	129.160***	4/6/83
8-month	1709	0.026	3.509	-18.685	20.227	-0.210	3.450	863.902***	5.191**	20.030***	75.138***	135.043***	11/9/83
9-month	1709	0.026	3.416	-17.105	19.625	-0.212	3.404	841.748***	4.919**	19.307***	80.148***	140.802***	11/9/83
10-month	1709	0.026	3.339	-15.603	19.088	-0.168	3.353	812.311***	4.627**	18.345***	80.426***	145.541***	11/9/83
11-month	1709	0.027	3.275	-15.425	18.801	-0.061	3.842	1056.723***	4.149**	16.648***	65.898***	125.291***	11/9/83
12-month	1703	0.032	3.349	-22.521	41.310	0.895	17.313	21554.673***	4.295**	14.558**	3.141*	6.403	12/21/83
						Panel B: Gold market returns							
Spot	1741	0.067	2.190	-12.383	13.703	-0.196	3.759	1040.451***	0.550	5.346	20.171***	82.174***	4/6/83
1-month	1741	0.068	2.232	-13.048	12.945	-0.247	4.202	1303.903***	0.203	3.540	19.944***	70.376***	4/6/83
2-month	1741	0.067	2.235	-13.106	13.102	-0.237	4.240	1325.564***	0.193	3.595	19.755***	69.620***	4/6/83
3-month	1741	0.067	2.240	-13.207	13.107	-0.239	4.218	1312.369***	0.178	3.899	19.823***	68.761***	4/6/83
4-month	1741	0.066	2.249	-13.351	12.981	-0.234	4.109	1245.738***	0.087	3.818	19.550***	64.583***	4/6/83
5-month	1741	0.066	2.263	-13.416	12.803	-0.338	4.523	1523.146***	0.188	3.305	16.442***	50.707***	4/6/83
6-month	1741	0.065	2.247	-13.480	12.580	-0.259	4.066	1223.397***	0.127	3.277	20.531***	64.907***	4/6/83
7-month	1741	0.064	2.245	-13.515	12.317	-0.270	4.043	1211.819***	0.128	3.238	21.032***	65.733***	4/6/83
8-month	1741	0.063	2.244	-13.590	12.090	-0.281	4.021	1200.538***	0.149	3.222	21.183***	66.023***	4/6/83
9-month	1741	0.063	2.242	-13.662	11.827	-0.291	3.992	1185.132***	0.145	3.243	21.531***	66.493***	4/6/83
10-month	1741	0.062	2.241	-13.756	11.632	-0.300	3.978	1178.518***	0.162	3.184	21.994***	67.299***	4/6/83
11-month	1741	0.061	2.239	-13.876	11.471	-0.310	3.975	1178.872***	0.175	3.099	22.546***	68.063***	4/6/83
12-month	1741	0.060	2.238	-14.015	11.240	-0.321	3.973	1179.443***	0.184	3.003	22.670***	68.555***	4/6/83

Note: Table reports the descriptive statistics for the spot and futures (1- to 12-monh) returns (in percent) for the oil (Panel A) and gold (Panel B) markets. Sample period starts at the period given in the last column of the table and ends at 8/10/16 at weekly frequency with n observations for each series. In addition to the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Bera normality test (JB), the Ljung-Box first [$Q(1)$] and the fifth [$Q(5)$] autocorrelation tests, and the first [ARCH(1)] and the fifth [ARCH(5)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH). The asterisks ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 2. Linear Granger causality tests

	H_0: Oil returns dos not Granger cause gold returns	Order of the VAR (p)
Spot	0.3515	1
1-month	0.4495	1
2-month	0.6243	1
3-month	0.4665	1
4-month	0.8578	1
5-month	0.9711	1
6-month	1.1388	1
7-month	1.3820	1
8-month	1.6680	1
9-month	1.7744	1
10-month	1.3677	1
11-month	0.6819	1
12-month	1.0793	1

Note: The table reports the F-statistic for the no Granger causality restrictions imposed on a linear vector autoregressive (VAR) model under the null hypotheses H_0. The order (p) of the VAR is selected by the Bayesian Information Criterion (BIC). ***, **, and * indicates rejection of the null of no Granger causality at 1%, 5%, and 10% level of significance respectively.

Table 3. [Brock *et al.* (1996)] BDS Test

	m=2	m=3	m=4	m=5	m=6
			Oil equation residuals		
Spot	4.3366***	6.3979***	8.7684***	12.0488***	16.0429***
1-month	2.8986***	4.6127***	6.4604***	8.9956***	12.0025***
2-month	2.7707***	4.5157***	6.5014***	9.0343***	12.3810***
3-month	2.8410***	4.5077***	6.5455***	9.0949***	12.4291***
4-month	2.7309***	4.4384***	6.2019***	8.4082***	11.2339***
5-month	3.0060***	4.7500***	6.5533***	8.9485***	12.0510***
6-month	2.6507***	4.4563***	6.4262***	9.0234***	12.1425***
7-month	2.6189***	4.5234***	6.6230***	9.2676***	12.3733***
8-month	3.0602***	5.1484***	7.3224***	10.2580***	13.7494***
9-month	3.1748***	5.3310***	7.5371***	10.4716***	14.1007***
10-month	3.2983***	5.4987***	7.9570***	11.0193***	14.8379***
11-month	3.3594***	5.5370***	7.9182***	10.8389***	14.5746***
12-month	3.6148***	5.5830***	7.8992***	10.8845***	14.5896***
			Gold returns equation residuals		
Spot	4.3366***	6.3979***	8.7684***	12.0488***	16.0429***
1-month	2.8986***	4.6127***	6.4604***	8.9956***	12.0025***
2-month	2.7707***	4.5157***	6.5014***	9.0343***	12.3810***
3-month	2.8410***	4.5077***	6.5455***	9.0949***	12.4291***
4-month	2.7309***	4.4384***	6.2019***	8.4082***	11.2339***
5-month	3.0060***	4.7500***	6.5533***	8.9485***	12.0510***
6-month	2.6507***	4.4563***	6.4262***	9.0234***	12.1425***
7-month	2.6189***	4.5234***	6.6230***	9.2676***	12.3733***
8-month	3.0602***	5.1484***	7.3224***	10.2580***	13.7494***
9-month	3.1748***	5.3310***	7.5371***	10.4716***	14.1007***
10-month	3.2983***	5.4987***	7.9570***	11.0193***	14.8379***
11-month	3.3594***	5.5370***	7.9182***	10.8389***	14.5746***
12-month	3.6148***	5.5830***	7.8992***	10.8845***	14.5896***

Note: The entries indicate the BDS test based on the residuals of oil series returns and gold series returns in a VAR for various sectors. *m* denotes the embedding dimension of the BDS test. ***, ** and * indicate rejection of the null of residuals being *iid* at 1%, 5%, and 10% levels of significance, respectively.

Table 4. [Diks and Panchenko (2006)] Nonlinear Granger Causality Test

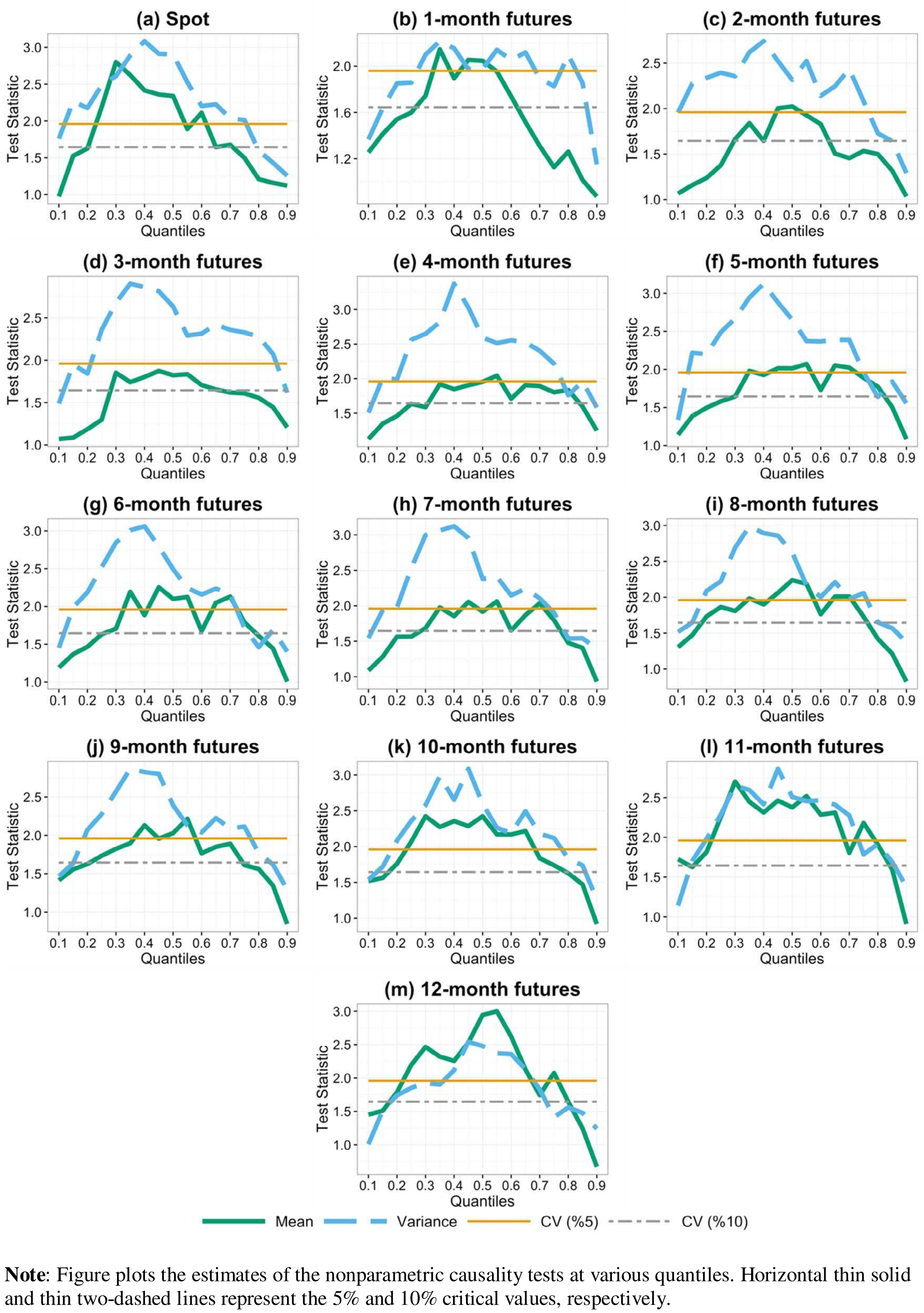
m=2		m=3		m=4	
Test statistic	p-value	Test statistic	p-value	Test statistic	p-value
1.255	0.105	0.640	0.261	0.041	0.484
0.762	0.223	-0.032	0.513	-1.231	0.891
0.579	0.281	0.249	0.402	-0.424	0.664
0.592	0.277	0.262	0.397	-0.583	0.720
0.537	0.296	-0.208	0.582	-0.156	0.562
-0.089	0.535	-0.246	0.597	0.008	0.497
0.436	0.331	0.060	0.476	0.273	0.393
0.552	0.291	0.028	0.489	0.564	0.286
0.730	0.233	-0.269	0.606	0.830	0.203
0.716	0.237	0.105	0.458	1.248	0.106
0.445	0.328	0.071	0.472	1.161	0.123
-0.132	0.553	-0.446	0.672	0.905	0.183
-0.828	0.796	-1.335	0.909	0.440	0.330

Note: m denotes the embedding dimension.

Figure 1. Time series plots of the spot and futures prices for the oil and gold markets

Note: Figure plots the natural logarithms of the price series.

Figure 2. Causality in mean and variance from the oil market series to the gold market series



Note: Figure plots the estimates of the nonparametric causality tests at various quantiles. Horizontal thin solid and thin two-dashed lines represent the 5% and 10% critical values, respectively.