International Journal of Economic Sciences and Applied Research 4 (3): 75-92

Testing for Linear and Nonlinear Causality between Crude Oil Price Changes and Stock Market Returns

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Abstract

This paper examines both the linear and nonlinear causal relationships between crude oil price changes and stock market returns for the United States. In particular, the study applied a battery of unit root tests to ascertain the time series properties of crude oil price changes and stock market returns. The linear and nonlinear causality tests were conducted through the standard VAR and the M-G frameworks, respectively. The results from both the linear and nonlinear unit root tests indicate that crude oil price changes and stock market returns are level stationary. The results from the standard VAR model provide evidence of bidirectional causality between crude oil price changes and stock market returns. The results from the M-G causality test support the finding of nonlinear bidirectional causality between crude oil price changes and stock market returns.

Keywords: Crude oil prices, nonlinear causality, stock market returns, BDS, structural breaks

JEL classifications: G10, G12, Q43

1. Introduction

An understanding of the relationship between high crude oil prices and stock markets is important to investors, financial analysts and policymakers. The conventional wisdom holds that high crude oil prices promote economic growth for oil exporting countries while on the other hand, stunts growth for oil importing countries. High oil prices decrease the amount of disposable income that consumers have available to spend on other goods and services. Furthermore, high oil prices lead to increases in the cost of production for non-oil producing firms. Increases in cost of production negatively affect the major determinants of stock market returns including corporate profits and dividends. The equity pricing model suggests that the price of equity at any given point in time is equal to the expected present value of the discounted future cash flows (Hung at al., 1996). Increases in crude oil prices are often associated with inflationary pressures. Thus, the central bank in an effort to avert

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the impending inflation increases interest rates. Increases in interest rates have direct effect on discount rates used in equity value calculation and hence lead to decreases in stock prices.

Given its importance in financial economics, a number of studies have examined the effect of high crude oil prices on stock markets. However, earlier studies on this issue lacked consensus relative to the impact of high crude oil prices on stock markets. For instance, Honarvar (2009), Lardica and Mignon (2008), Anoruo and Mustafa (2007), and Huang et al., (1996) found significant relationship between high crude oil prices and stock markets. However,

Al-Fayoumi (2009), Sari and Soytas (2006) and Maghyereh (2004) found that high crude oil prices have no significant effect on stock markets. Honarvar (2009) using the Crouching Error Correction Model examined the relationship between retail gasoline and crude oil prices for the U.S. He found evidence of cointegration between positive components of crude oil and negative components of gasoline prices. Based on this finding he concluded that in the long run that gasoline prices are more influenced by technological changes on the demand side than crude oil price movements on the supply side. Lardic and Mignon (2008) examined the long run relationship between crude oil prices and economic activity using asymmetric cointegration procedures for the U.S. economy, the G7, Europe and the Euro area economies. They found evidence of asymmetric cointegration between oil prices and GDP. However, they failed to reject the null hypothesis of no linear cointegration between oil prices and GDP. Anoruo and Mustafa (2007) examined the relationship between oil and stock market returns for the United States using cointegration techniques and the vector error correction model (VECM). They found that oil and stock market returns are cointegrated. Using the VECM they also found that causality runs from stock market returns to oil market returns but not vice versa. Based on these results, they concluded that the two markets are integrated rather than segmented. They interpreted the finding of cointegration between oil and stock market returns as evidence that investors cannot benefit from diversification by holding assets in oil and stock markets simultaneously.

Ciner (2001) examined the relationship between crude oil prices and stock market for the United States using the Hiemstra-Jones (1994) nonlinear Granger causality test. He found evidence that crude oil prices and the stock market returns are nonlinearly related. Ciner blamed the inability of the earlier studies to find significant relationship between crude oil prices and stock market returns on their use of linear models. Similarly, Sadorsky (1999) found that oil price shocks have significant implications for stock market returns. Jones and Kaul (1996) examined the relationship between oil prices and equity markets. They found that oil price shocks have significant effect on stock market returns for the United States. Huang, et al. (1996) using the VAR model examined the relationship between daily oil futures return and stock market returns for the United States. They found evidence of Granger causality running from daily oil futures return to stock of individual oil companies. However, they failed to find evidence of causality running from daily oil futures return to stock market returns (proxied by the S&P 500). Kaul and Seyhun (1990) investigated the relationship between real stock market returns and the volatility of oil prices. They found that there is a significantly negative relationship between real stock returns and oil price volatility.

On a related study, Peri and Baldi (2010) using the threshold cointegration technique examined the long-run relationship between vegetable oil prices and conventional diesel prices in the European Union for the period spanning 2005 through 2007. In particular, they explored the issue of asymmetric dynamics between the prices of rapeseed oil, sunflower oil, and soybean oil, and the price of diesel. They found evidence in support of a two-regime threshold cointegration between the rapeseed oil price and the diesel price, but not for the other pairs. They therefore concluded that the rapeseed oil price responds asymmetrically to deviations from its long-run equilibrium with fossil diesel prices. Al-Fayoumi (2009) examined the relationship between changes in oil prices and stock market returns for three oil importing countries including Turkey, Tunisia and Jordan using the VECM. He failed to find evidence supportive of the notion that oil prices have predictive power on stock market returns for the sample countries. He therefore recommended that the authorities and portfolio managers should concentrate on other macroeconomic factors like interest rate and industrial production rather than oil prices in forecasting movements in stock market returns.

Bekiros and Diks (2008) examined the linear and nonlinear causal relationships between daily spot and futures prices for maturities of one, two, three and four months of West Texas Intermediate crude oil. They found that the linear causal relationships between daily spot and futures prices for maturities of one, two, three and four months crude oil prices tend to disappear after VECM cointegration filtering. In addition, they found that the nonlinear causal relationships in some cases persisted even after GARCH filtering in both periods which they considered. Based on these findings, they concluded that spot and futures returns might exhibit asymmetric GARCH effects. They also find that neither the spot market nor the futures market leads or lags the other consistently over time. In other words, the pattern of leads and lags was found to change with time. Sadorsky (2008) examined the relationship between oil price changes, firm size, and stock prices. Specifically, he investigated whether movements in oil prices have larger or smaller effects on the stock prices of small- or medium-sized firms. He found evidence that the relationship between oil price fluctuations and stock prices varied with the size of the firm. He further found that the relationship between oil price movements and medium-sized firms is the strongest.

Hammoudeh and Choi (2006) examined the relationships between stock markets and three global factors (i.e. the WTI oil prices, the U.S. 30-months Treasury bill rate and the S&P Index) for five members of the Gulf Cooperation Council. They failed to find evidence of direct impact of oil prices on the S&P 500 index. Agren (2006) investigated the volatility transmission between oil prices and stock markets using the GARCH model for Japan, Norway, Sweden, the U.K. and the U.S. He found evidence supportive of volatility transmission between oil prices and the stock markets for the sample countries. Sari and Soytas (2006) examined the relation of oil price shocks to real returns in Turkish stocks that traded on the Istanbul Stock Exchange market. They found evidence that oil price shocks do not have significant impact on real stock returns for Turkey. Maghyereh (2004) using the VAR model investigated the relationship between crude oil price shocks and stock market returns for 22 emerging economies. Based on the results from the VAR model, he concluded that crude oil price shocks have no implications for stock market returns for the sample emerging economies.

Unlike most of the earlier studies that relied on linear models in examining the relationship between crude oil prices and stock market returns, the present study applies a more recent nonlinear causality test that is capable of conditioning on the samples of the causing variable being either positive or negative. In addition, the study uses longer time series spanning from February 1974 through December 2009. Given the length of the study period, the paper also applies the Bai and Perron (1998, 2001, 2003) procedures to search for possible structural breaks in the data.

The remainder of the paper is organized as follows. After the present introduction, section 2 provides the methodology. Section 3 describes the data and provides descriptive statistics. Section 4 reports empirical results of the study. Finally, section 5 offers the summary and policy implications.

2. Methodology

This study applies the modified Dickey and Fuller (DF-GLS) unit root test developed by Elliot et al. (1996). The DF-GLS procedure has been shown to have better power than the conventional Dickey-Fuller (Elliot et al. 1996). The DF-GLS unit root test is based on the following regression equation:

$$\Delta X_t^k = \alpha_0 X_{t-1}^k + \sum_{j=1}^{m} \alpha_j \Delta X_{t-j}^k + \mu_t \tag{1}$$

where m is the maximum lag, X_t^k represents locally detrended series of X_t [i.e. $X_t^k = X_t - z_t\widetilde{\alpha}$, where zt = (1,t) and $\widetilde{\alpha}$ is the regression of $\hat{X}$ on $\hat{z}$]. The Modified Akaike Information Criterion proposed by Ng and Perron (2002) is used to determine the maximum lag lengths for the various time series in the system. The DF-GLS unit root test involves testing the null hypothesis that $\alpha_0 = 0$ against the alternative that $\alpha_0 < 0$, in equation (1).

2.1 Linear Granger Causality Test

To test for linear causality between crude oil price changes and stock market returns, the study implements the standard VAR model. Causality tests are based on the seminal work of Granger (1969). The following VAR models are estimated to ascertain the causal relationships between crude oil price changes and stock market returns:

$$SMR_t = \alpha + \sum_{i=1}^{a} \beta_i SMR_{t-1} + \sum_{j=1}^{b} \varphi_j COP_{t-1} + \mu_t \tag{2}$$

$$COP_t = \alpha + \sum_{i=1}^{a} \beta_i SMR_{t-1} + \sum_{j=1}^{b} \varphi_j COP_{t-1} + \mu_t \tag{3}$$

where SMR represents stock market returns, *COP* stands for crude oil price changes, a and b are the maximum lag orders determined by the Akaike Information Criterion. The error term is represented by μ in equations (2) and (3). In equation (2), crude oil price changes have causal influence on stock market returns, if the regression coefficients on *COP* are jointly statistically different from zero. In either case, the null hypothesis that crude oil price changes do not Granger-cause stock market returns is rejected. The joint significance of the regression coefficients on *COP* implies that crude oil price changes are important in predicting movements in stock market returns. Similarly, the null hypothesis that stock market returns do not have causal implications for crude oil price changes is rejected if the regression coefficients on *SMR* in equation (3) are jointly significant at the conventional levels. The *F*-test is used to determine the joint significance of the variables in the VAR models.

2.2 BDS Nonlinearity Test

Prior to applying the M-G causality tests, the study implements the BDS nonlinearity test proposed by Brock et al. (1987, 1996) to determine the existence of nonlinear dependence in the data. The BDS test is applied to the residual of the series of interest. Nonlinearity is indicated if the test statistic is greater than the critical value for the standard normal distribution at the conventional levels. The BDS nonlinearity test is based on the correlation integral of the time series as follows:

$$\mathrm{W}_m(\varepsilon, T) = \frac{\sqrt{T}[C_m(\varepsilon,T) \; - \; C_1(\varepsilon,T)^m]}{\sigma_m(\varepsilon,T)} \tag{4}$$

where $\mathrm{W}_m(\varepsilon,\mathrm{T})$ represents the BDS test statistic, $\sigma_m(\varepsilon,\mathrm{T})$ stands for the standard deviation of $\mathrm{C}_m(\varepsilon,\mathrm{T})$, m is the embedding dimension, while ε represents the maximum difference between pairs of observations considered in calculating the correlation integral. The BDS test statistic is asymptotically normally distributed with zero mean and unit variance [i.e. *N*(0,1)]. The null hypothesis of the BDS procedure is that the data are independently, identically distributed (i.i.d). The null hypothesis of linearity is rejected if the computed test statistic exceeds the critical value at the convention level. The rejection of the null hypothesis reveals the presence of nonlinear dependence in the data.

2.3 Bai and Perron Test for Multiple Structural Beaks

To address the issue of possible structural breaks in the data, the paper applies the Bai and Perron (1998, 2001, 2003) procedures. Structural break testing is important in this paper for two reasons. First, the paper employed longer time series starting from January 1974 and ending in December 2009. Second, structural breaks have been cited in the literature as one of the sources of nonlinearity in economic and financial time series

(Kyrtsou 2011, pp. 3). The Bai and Perron multiple structural break procedures involve three tests including the SupF type, the double maximum statistics – Udmax and WDmax, and the SupF(l+1|l). The procedures involve regressing the variable of interest (Y) on a constant and then test for structural breaks. The tests are based on the following model with m breaks (m+1 regimes):

$$Y_t = \beta_t + \mu t \text{, for } t = T_{j-1} + 1, \ldots, T_j, j = 1, \ldots m+1 \tag{5}$$

where Y_t is a stationary variable in period t. β_t represents the mean variable in the j_{th} regime. $T_1, \ldots, T_m$ are indices that represent the break points, which by assumption are unknown. In equation (5), y is estimated through ordinary least squares technique. Bai and Perron (1998) consider an *F*-statistic of the type given below:

$$SupF_T(b) = F_T(\lambda_1 \ldots \ldots, \lambda_b), \tag{6}$$

where $\lambda_1 \ldots \ldots, \lambda_b$ minimize the global sum of squared residuals $S_T(T\lambda_i)$ with I = 1,…,b (b is the number of breaks detected by the testing procedure). The paper assumes five structural breaks (i.e. M=5) in the data with a trimming factor of 0.15. To test the null hypothesis of no breaks in the time series against the alternative of an unknown number of breaks given an upper bound M, Bai and Perron (1998) proposed two test statistics known as the double maximum statistics (i.e. Udmax and WDmax). The Udmax procedure is given by the expression:

$$UDmax = {}_{max1 \leq m \leq M} SupF_T(m) \tag{7}$$

In addition, Bai and Perron consider a different set of weights in such a way that the marginal p-values are equal for all values of m. This particular type of test is denoted as the WDmax. To determine the number of structural breaks in the data, Bai and Perron suggest that the researcher should first examine the results from the Udmax and WDmax to see if at least one structural break exists. The break points are then selected by examining the test statistics from the SupF(l+1|l) procedures which involve sequential testing of the null hypotheses against various alternatives. For instance, the null hypothesis of l breakpoint is tested against the alternative hypothesis of l+1breakpoints. Depending on the results from the SupF(l+1|l) techniques, the Schwarz Information Criterion (BIC), the modified Schwarz Information Criterion (LWZ) (Liu,Wu, and Zidek (1994) and the sequential procedures can be used to select the exact number of structural breaks in the data.

2.4 Nonlinear Granger Causality Test

Hiemstra and Jones (1993) point out that one of the shortcomings of the linear causality tests involves their inability to detect the nonlinear relationships between macroeconomic variables. In addition to linear linkages, many financial time series including crude oil prices and stock market returns may be related in a nonlinear fashion. Kyrtsou and Labys (2006) suggest that a small change in one variable can produce multiplicative and disproportionate impact on the variables in the presence of nonlinearity.

This paper applies the bivariate noisy Mackey-Glass (M-G) model proposed by Kyrtsou and Terraza (2003, Kyrtsou and Labys (2006) to determine the nonlinear causal relationship between crude oil price changes and stock market returns. The M-G nonlinear causality tests are based on the following:

$$X_t = a_{11}\frac{X_{t-\tau i}}{1+X_{t-\tau i}^{c1}} - \delta_{11}X_{t-1} + a_{12}\frac{Y_{t-\tau 2}}{1+Y_{t-\tau 2}^{c2}} - \delta_{12}X_{t-1} + \mu_t\ ;\ \mu \sim \mathrm{N}(0,1) \tag{8}$$

$$Y_t = a_{21}\frac{X_{t-\tau i}}{1+X_{t-\tau i}^{c1}} - \delta_{21}X_{t-1} + a_{22}\frac{Y_{t-\tau 2}}{1+Y_{t-\tau 2}^{c2}} - \delta_{22}X_{t-1} + \mu_t\ ;\ \mu \sim \mathrm{N}(0,1) \tag{9}$$

In equations (8) and (9) α and δ are parameters to be estimated. τ represents the delay parameter and c is a constant. Under the M-G framework, the parameters τ_1, τ_2, c_1, and c_2 are selected a priori. The Schwarz criterion is used to determine the optimal delay parameters including τ_1 and τ_2. The M-G nonlinear causality test involves testing whether the past values of a variable such as *Y* have predictive non-linear impact on the current value of another variable such as *X* and vice versa. The M-G nonlinear causality technique has a number of advantages over the conventional VAR model. First, the M-G technique has the ability to filter more difficult dependent dynamics in time series. Second, the M-G nonlinear causality model allows the researcher to isolate the effects of either negative or positive values of the independent variable on the dependent variable. For example, using the M-G asymmetric model the impact of positive/negative crude oil price shocks on stock market returns can be examined. The null hypothesis that y does not M-G cause x is $\alpha_{12} = 0$. The null hypothesis is rejected if the *F*-statistic is greater than the critical value at the conventional levels. Details of the M-G framework can be found in Kyrtsou and Terraza (2003) and Kyrtsou and Labys (2006).

3. Data and Descriptive Statistics

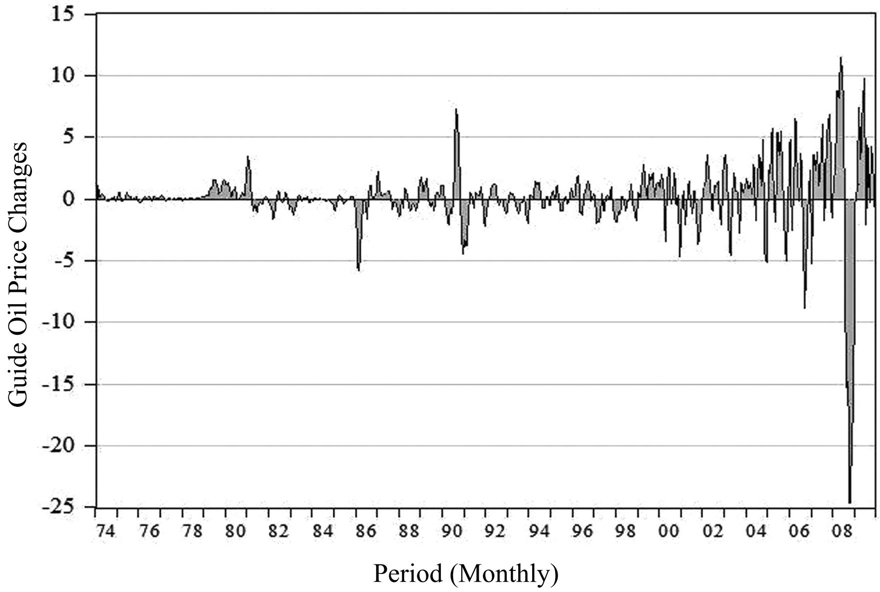
The data used in this study consist of monthly observations on nominal crude oil prices and the S&P 500 index (proxy for stock market). The stock market return series are calculated as percentage changes in the S&P 500 index. Crude oil price changes are obtained by $(y_t–y_{t-1})$. The sample period covers February 1974 through December 2009. Crude oil price data were collected from the *US Energy Information Administration* (EIA) website at (http://tonto.eia.doe.gov/dnav/pet/pet_cons_top.asp). The stock market data were retrieved from Finance Yahoo at (http://finance.yahoo.com).

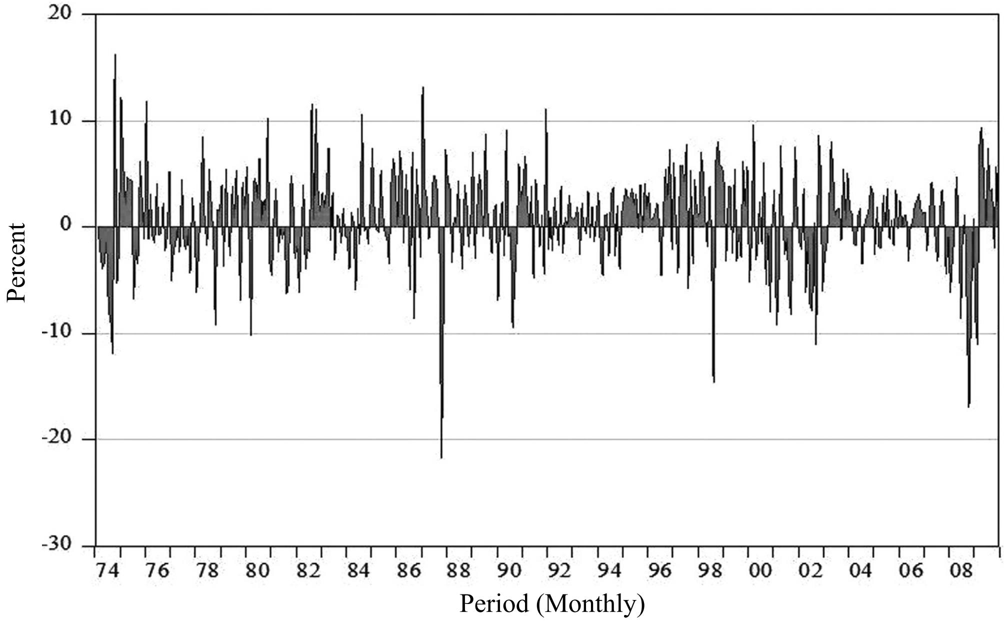
Table 1: Descriptive Statistics

Statistics	*COP*	*SMR*
Mean	0.152	0.672
Maximum	11.550	16.305
Minimum	-24.690	-21.763
Standard Deviation	2.922	4.543
Skewness	-2.787	-0.465
Kurtosis	26.459	4.993
Jarque-Bera	10440.600***	86.870***
Probability	0.000	0.000
Observations	431	431

*** rejection of normality assumption at the 1% level of significance. *COP* = crude oil price changes, *SMR* = stock market returns (S&P500).

Table 1 presents the descriptive statistics for crude oil price changes and stock market returns. The mean return values are 0.152 and 0.672, respectively for crude oil price changes and stock market returns. The minimum and maximum values indicate that the return series varied during the period under consideration. For instance, crude oil price changes varied from a minimum of -24.690 to a maximum of 11.550. The stock market return series exhibited the greatest variability (4.543%) from the mean as indicated by the standard deviation. Both crude oil price changes and stock market returns are negatively skewed. The skewed statistics ranged from -2.787 for crude oil price changes to -0.456 for stock market returns. The crude oil price changes and stock market returns exhibited excess kurtosis. However, the excess kurtosis for crude oil price changes (26.459) is more pronounced than that of stock market returns (4.993). Based on the Jarque-Bera statistics, the null hypothesis that crude oil price changes and stock market returns are normally distributed is rejected at the 1 percent significance level in all of the cases. Figures 1 and 2 plot the crude oil price changes and stock market return series. These graphs reveal that stock market returns exhibit more volatility than crude oil price changes. This observation is consistent with the standard deviations displayed in Table 1.





4. Empirical Results

The empirical analysis of the study begins with unit root testing. In particular, the study ascertains the time series properties of crude oil price changes and stock market returns by applying a battery of unit root testing procedures including the conventional

ADF (Dickey-Fuller, 1981), the modified ADF (DF-GLS), the KPSS (Kwiatkowski, et. al., 1992) and the NLADF (Kapetanios, et al., 2003). The unit root tests were first conducted with a constant and then with a constant and time trend. Table 2 displays the results from the various unit root testing procedures. The results indicate that crude oil price changes and stock market returns are level stationary at the 1 percent significance level. In each case, the test statistics from the ADF, DF-GLS, KPSS and KSS unit root procedures exceed the critical values at least at the 10 percent level of significance. For the KPSS unit root procedures, the test statistics are less than the critical values, indicating that the null hypothesis of stationarity should not be rejected at the 1 percent level of significance.

Table 2: Linear and Non-Linear Unit Root Test Results

Series	*ADF*	*DF_GLS*	*KPSS*	*NLADF*
Panel A: Tests with Constant				
COP	-9.867(1)***	-9.159(1)***	0.079(1)***	-3.351(1)*
SMR	-14.687(1)***	-13.909(1)***	0.153(1)***	-5.720(1)***
Panel B: Tests with Constant and Trend				
COP	-9.684(1)***	-9.472(1)***	0.038(1)***	-3.351(1)*
SMR	-14.692(1)***	-14.387(1)***	0.114(1)***	-5.720(1)***

The 1%, critical values for the ADF and DF-GLS with a constant are -3.9835. For KPSS the 1% critical value is 0.739. For with a constant and a time trend, the 1%, critical values for the ADF and DF-GLS with a constant are -3.448 while that for the KPSS is 0.1260. The critical values for the NLADF unit root tests at the 1, 5 and 10% levels are -3.90, -3.4 0 and -3.13, respectively. *COP* = crude oil price changes, *SMR* = stock market returns (S&P500).

Having determined that the series are level stationary, the study next applies the linear Granger causality tests. The Granger causality test results based on the standard VAR models are presented in Table 3. The results suggest that the null hypothesis that stock market returns do not Granger-cause crude oil price changes should be rejected, since the test statistic (*F-Statistic* = 4.516) exceeds the critical value (CV=3.863) at the 5 percent significance level. Similarly, the results indicate that the null hypothesis that crude oil price changes do not Granger-cause stock market returns should be rejected. Again, the test statistic (*F-Statistic* = 6.815) exceeds the critical value (CV=3.863) at the 5 percent significance level. Taken together, the results from the linear Granger causality tests reveal that there is a feedback relationship between crude oil price changes and stock market returns. In other words, the two time series reinforce one another.

Table 3: Linear Granger Causality Tests

Null Hypothesis:	*Obs*	*F-Statistic*	*5%CV*
SMR → *COP*	428	4.516**	3.863
COP → *SMR*	428	6.815**	3.863

** indicates rejection of the null hypothesis of noncausality at the 5% significance level. *COP* = crude oil price changes, *SMR* = stock market returns (S&P500). Optimal lag of 3 was determined by the AIC.

In addition to linear causal relationship between crude oil price changes and stock market returns, the study explores the possibility that the two time series might also have nonlinear influence on each other. One of the frequently cited weaknesses of the standard Granger causality test is its inability to detect nonlinear relationships between variables. In other words, the conventional Granger causality test is essentially designed to capture linear relationships among macroeconomic variables. However, a number of studies have shown that the relationship between crude oil prices and stock market returns tend to be nonlinear. For example, Ciner (2001) using the Hiemstra-Jones (1994) framework found that oil prices and the stock market are nonlinearly related for the United States. Similarly, Hamilton (1996, 2000) found for the United States that oil shocks and output are nonlinearly related. If indeed crude oil price changes and stock market returns are nonlinearly related, results from the linear Granger causality test would be biased. In either case, wrong inferences pertaining to the relationship between the two variables would have been drawn. To avoid spurious inferences, this study applies the M-G nonlinear causality tests.

Prior to testing for M-G nonlinear causality between crude oil price changes and stock market returns, the study applies the BDS nonlinearity test developed by Brock et al. (1987). Table 4 displays the p-values for the BDS nonlinearity tests. The results reveal that the null hypothesis of linearity should be rejected at the 1 percent level of significance for both crude oil price changes and stock market returns. The optimal lag lengths (m) were automatically determined within the model.

Table 4: Linearity Test Results (*P*-Values)

Series	*BDS*	*MCLEOD*	*WHITE*	*M*
COP	0.000***	0.000***	0.000***	5
SMR	0.007***	0.001***	0.081*	1

***, **, * indicate rejection of nonlinearity hypothesis at the 1%, 5% and 10% levels, respectively. *COP* = crude oil price changes, *SMR* = stock market returns (S&P500).

To check the robustness of the BDS test results, the study also implemented the McLeod and the White (1989) nonlinearity tests. The results from the McLeod and the White nonlinearity tests presented in Columns 3 and 4 of Table 4 suggest that the null hypothesis of linearity in crude oil price changes and stock market returns should be rejected at least, at the 10 percent significance level. These results are consistent with those provided by the BDS procedure. Taken together, the results from the three nonlinearity tests indicate that crude oil price changes and stock market returns are nonlinear.

Table 5: Bai and Perron Test for Structural Breaks

Statistics	*COP*	*SMR*
$SupF_T(1)$[a]	0.1950	3.7920
$SupF_T(2)$	1.9488	4.2818
$SupF_T(3)$	2.0045	4.0257
$SupF_T(4)$	1.6043	3.9090
$SupF_T(5)$	1.6487	2.6369
UDmax[b]	2.0045	4.2818
WDmax[c]	3.6179	6.7212
$SupF_T(2/1)$[d]	3.7795	4.2811
$SupF_T(3/2)$	1.6139	2.4478
$SupF_T(4/3)$	0.1689	2.4747
$SupF_T(5/4)$	—	—
No of Break(s) Selected		
BIC	0	0
LWZ	0	0
Sequential	0	0
Break Dates	None	None

COP = crude oil price changes, *SMR* = stock market returns (S&P500).

a. The critical values for the supF tests at the 5%(10%) level for 5 breaks are 8.5800(7.0400), 7.2200(6.2800), 5.9600(5.2100), 4.9900(4.4100), and 3.9100(3.4700).

b. The critical values for the UDmax tests at the 5%(10%) level are 8.8800(7.4600).

c. The critical values for the WDmax tests at the 5%(10%) level are 9.9100(8.2000).

d. The critical values for the supF(l+1/l) (forl=1 to 5 breaks) tests at the 5%(10%) level are 8.5800(7.0400), 10.1300(8.5100), 11.1400(9.4100), 11.8300(10.040), and 12.2500(10.5800).

The study next implements the Bai and Perron multiple structural break tests to determine whether the crude oil price changes and stock market return series are structurally stable. The results from the Bai and Perron tests are presented in Table 5. The results from the SupF procedure reveal the absence of structural breaks in both stock market returns and crude oil price changes. In each case, the test statistic is statistically insignificant. Similarly, the test statistics for the double maximum (i.e. UDmax and WDmax) procedures which test the null hypothesis of no structural break against the alternative of an unknown number of breaks are statistically insignificant at the conventional levels. For crude oil price changes, the test statistics 1.6487 and 2.0045, respectively for the UDmax and WDmax procedures are less that the critical values (7.4600 and 8.2000) at the 10 percent level of significance. For stock market returns, the test statistics for the UDmax and WDmax are 4.2818 and 6.7212, respectively. Again, the test statistics are all less than the critical values at the 10 percent level, confirming the absence of structural changes in the data. The test statistics for the SupF(l+1/l) procedures are all insignificant for both crude oil price changes and stock market returns. The test statistic in each case is less than the critical value at the 10 percent level of significance. Given the insignificance of the test statistics from the SupF(l+1/l) procedures, the BIC, LWZ, and the sequential procedures selected zero structural breaks for both crude oil price changes and stock market returns. Taken together, the results from the SupF, UDmax,WDmax and SupF(l+1/l) suggest that crude oil price changes and stock market returns are structurally stable for the study period.

Table 6: Nonlinear Causality Test Results (Symmetric Case)

Null Hypothesis:	*F-Statistic*	*P-value*
SMR → *COP*	0.072	0.789
COP → *SMR*	5.607**	0.018

** indicates rejection of the null hypothesis of noncausality at the 5% significance level. *COP* = changes in oil prices, *SMR* = stock market returns (S&P500). The parameters for the M-G model are as follows: τ_1= 10, τ_2= 1, c_1=4, and c_2=1.

Given that crude oil price changes and stock market returns are nonlinear and structurally stable, the study next implements the M-G causality tests to determine the causal relationship between the two time series. Table 6 presents the results from the symmetric version of the M-G nonlinear causality test whereby the entire sample of the causing variable is used. In other words, the causing variable (in our case, crude oil price changes) is not conditioned on being positive or negative. The results suggest that the null hypothesis that stock market returns do not M-G cause crude oil price changes should be accepted based on the test statistic (F = 0.072, pv = 0.789) which is not statistically significant at the conventional levels. However, the results indicate that the null hypothesis that crude oil price changes do not M-G cause stock market returns should be rejected. The F-static (12.738, pv = 0.000) is statistically significant at the 1 level.

Table 7 displays the results from the asymmetric M-G causality tests, in which case the causing variable (i.e. crude oil price changes) is conditioned on being negative. The results indicate that the null hypothesis that stock market returns do not have nonlinear causal influence on crude oil price changes should not be rejected as the test statistic (F =0.275, pv = 0.600) is statistically insignificant. However, the null hypothesis that positive values of crude oil price changes do not M-G cause stock market returns should be rejected given that the test statistic (F = 12.738, pv = 0.000) is statistically significant at the 1 percent level.

Table 7: Nonlinear Causality Test Results (Asymmetric Case for Negative Crude Oil Price Changes)

Null Hypothesis:	*F-Statistic*	*P-value*
$SMR \rightarrow COP$	0.275	0.600
$COP \rightarrow SMR$	12.738^{***}	0.000

*** indicates rejection of the null hypothesis of noncausality at the 1% significance level. *COP* = changes in oil prices, *SMR* = stock market returns (S&P500). The parameters for the M-G model are as follows: τ_1= 1, τ_2= 1, c_1=c_2=2.

Table 8 presents the results obtained from the asymmetric M-G causality test conditioned on the values of crude oil price changes being positive. The results suggest that the null hypothesis that stock market returns do not M-G cause crude oil price changes should be rejected. The test statistic (F=2.929, pv=0.088) is statistically significant at the 10 percent level. Similarly, the null hypothesis that positive values of crude oil price changes do not M-G cause stock market returns should be rejected. The test statistic (F = 10.600, pv = 0.001) is statistically significant at the 1 percent level. Taken together, the results presented in Tables 8 indicate that there is a bidirectional relationship between positive values of crude oil price changes and stock market returns for the United States for the period under study.

Table 8: Nonlinear Causality Test Results (Asymmetric Case for Positive Crude Oil Price Changes)

Null Hypothesis:	*F-Statistic*	*P-value*
$SMR \rightarrow COP$	2.929^{*}	0.088
$COP \rightarrow SMR$	10.600^{***}	0.001

*** and * indicate rejection of the null hypothesis of noncausality at the 1% and 10% significance levels, respectively. *COP* = changes in oil prices, *SMR* = stock market returns (S&P500). The parameters for the M-G model are as follows: τ_1= 1, τ_2= 1, c_1=c_2=2.

The finding that crude oil price changes have nonlinear causal influence on stock market returns is consistent with Ciner (2001) who used the Hiemstra and Jones (1994) nonlinear Granger causality test. However, it must be pointed out that unlike Ciner (2001), the present study applied a more powerful test which allows the causing variable to be conditioned on being positive or negative. In addition, Ciner (2001) considered only the symmetric relationship between crude oil price changes and stock market returns. The present study, however, examined both the symmetric and asymmetric relationships between the two time series. An interesting finding that emerges from Tables 7 and 8 is that stock market returns respond asymmetrically to both positive and negative shocks to changes in crude oil prices. However, crude oil price changes respond nonlinearly to only positive shocks to stock market returns.

5. Summary and Implications

This paper has examined the linear and nonlinear causal relationships between crude oil price changes and stock market returns for the United States. In particular, the study used linear (i.e. ADF, DF-GLS and the KPSS) and the nonlinear (i.e. NLADF) unit root tests to determine the time series properties of both crude oil price changes and stock market returns. For linear Granger causality test, the study applied the standard VAR models. However, in order to test for nonlinear causal relationship between crude oil price changes and stock market returns, the study implemented both the symmetric and asymmetric versions of the M-G framework. Prior to testing for nonlinear causality between the two variables, the BDS, McLeod and White nonlinearity tests were implemented to test for linear dependencies in the variables. The study further applied the Bai and Perron multiple structural break tests to examine the stability of crude oil price changes and stock market returns for the study period.

The results from the various unit root tests indicate that crude oil price changes and stock market returns are level stationary. The results from the standard Granger causality tests provide evidence of bidirectional causality between crude oil price changes and stock market returns. The results obtained from the BDS, McLeod and White tests indicate that crude oil price changes and stock market returns are nonlinear. The results from the Bai and Perron procedures reveal that crude oil price changes and stock market returns are structurally stable for the period under investigation. The results from the symmetric M-G causality test indicate that nonlinear causality runs from crude oil price changes to stock market returns, but not vice versa. When the M-G test is conditioned on the negative values of crude oil price changes, there was found evidence of causality running from crude oil price changes to stock market returns but not vice versa. However, when the M-G causality test is conditioned on the positive values of crude oil price changes, the results provided evidence of a bidirectional causal relationship between crude oil price changes and stock market returns. The major finding of this study is that oil and stock markets are integrated rather than segmented as suggested by the feedback relationship between crude oil price changes and stock market returns. From investment perspective, the results indicate that the oil and stock markets are not efficient as the past values of one can be used to predict movements in the other.

Acknowledgments

The author is grateful to Dr. Catherine Kyrtsou for graciously providing the Matlab codes to implement the nonlinear causality tests. The author also appreciates the insightful comments and suggestions by two anonymous referees and the participants at the 70th IAES conference. The author is responsible for any errors in the paper.

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