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The Relationship between World Stock Markets and Oil Prices: A Nonlinear Analysis

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ABSTRACT

Purpose – The research investigates the correlation between international stock markets and crude oil prices. Various classifications of indexes, such as those for established, emerging, and frontier markets, have been used for this objective. The objective of the research is to determine the correlation between several regional indicators and oil prices.

Design/Methodology/Approach – The study covers weekly data for the period from January 7, 2018, to October 8, 2023. In the study, non-linear unit root tests, specifically the BDS test, as well as the tests proposed by Sollis (2009) and Hu and Chen (2016), have been employed. The study examines the non-linear causation framework by employing the methodology introduced by Diks and Panchenko (2006) to analyze the association between WTI oil prices and Morgan Stanley Capital Index (MSCI) indices.

Findings - The study reveals the presence of uni-directional non-linear causality between WTI oil prices and developed and frontier market indices. Additionally, bi-directional non-linear causality is detected between WTI oil prices and the emerging market index. The study revealed the presence of a bidirectional non-linear causality relationship between Brent oil prices and developed and emerging MSCI stock market indices. However, a unidirectional non-linear causality is seen between the frontier stock market index and Brent oil price.

Discussion - The findings may help investors, academics, and regulators. The study's indices of stock markets with various levels of global development may help investors in different countries. First, investors should consider the nonlinear relationship between oil prices and stock markets when developing portfolio management and risk hedging methods. They should start models and plans with nonlinearity. Investors may reduce risk by monitoring the stock-oil price relationship. Oil price changes should concern policymakers. They must account for nonlinear connections if oil prices rise or fall.

1. INTRODUCTION

Oil has a crucial role in the worldwide economy. The acknowledgement of the influence of crude oil price changes on the economic growth of nations has been documented (Santillán-Salgado, Calderón Villarreal and Venegas-Martínez, 2017; Dutta, Noor and Dutta, 2017). The volatility in energy prices has a significant influence on economic and financial markets through various routes and at different levels. Crude oil has become a notable indication of economic and financial factors in both advanced and emerging market countries (Tiwari et al., 2019).

Oil price fluctuations are regarded as a significant factor influencing global finance (Naifar and Al Dohaiman, 2013). The volatility of oil prices has a propensity to initiate a series of reactions on the financial markets, which are reflected in the MSCI indexes. For example, businesses that are highly dependent on petroleum inputs may have increased production costs in response to a rise in oil prices; this might possibly have an effect on the stock prices of corporations operating in these sectors. In contrast, sectors that gain from reduced production expenses might potentially perceive a decline in oil prices as advantageous, so exerting an alternative impact on stock prices. The increase in energy costs might lead to a decrease in stock prices and the emergence of industrial methods that are less dependent on petroleum inputs. According to Karacaer-Ulusoy and Kapusuzoglu (2017), the increase in oil prices has had a detrimental effect on economic development, leading to a state of stagnation in national economies.

The influence of oil prices on an economy may be quantified through the use of stock markets (Hanif, 2020). The correlation between oil price volatility and stock market volatility is evident (Degiannakis, Filis and Arora,

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2018). Investors are highly responsive to oil price variations, and hence, stock market fluctuations have a substantial impact on their investment choices (Ghosh and Kanjilal, 2016). Investors attuned to the complex relationship between oil prices and market dynamics should closely monitor MSCI indices to gauge the potential impact on their investment portfolios. These indexes furnish an all-encompassing perspective on the manner in which various areas react to variations in oil prices, hence furnishing crucial data for the formulation of strategic investment strategies.

The Morgan Stanley Capital International (MSCI) indexes serve as benchmarks for assessing the performance of global stock markets. These indexes are crucial for investors to assess and express the risks linked to the stock markets of different nations. When creating MSCI indices, factors such as the extent to which stock prices represent a given nation, the capacity to replicate the index, and the efficiency of the process are taken into account (MSCI Index Policies, 2018). These indices are used by stock market investors, portfolio managers, brokerage firms, researchers, and individuals. MSCI indices are evaluated and monitored by investors in international portfolio investments. Reviewing and updating the stocks comprising MSCI indices on a regular basis is necessary to ensure that they accurately reflect market dynamics.

The complex relationship between oil prices and international financial markets has been more evident in recent decades, as seen by the proliferation of widely utilized benchmarks like the Morgan Stanley Capital International (MSCI) indexes. The MSCI index, which is extensively employed as a standard in international stock markets, symbolizes the performance of firms spanning several industries and geographies. Conversely, oil prices exert a substantial influence on worldwide economies by virtue of their impact on consumer spending, inflation, and manufacturing expenses. Investors may gain significant insights into market patterns and prospective investment opportunities through the interaction of these two elements (Kang, Ratti and Yoon, 2015).

The price of crude oil exerts a substantial impact on the financial markets of nations, consequently echoing across other industries and ultimately determining their economic health. The MSCI indexes, which are intended to symbolize distinct market groups (developed, developing, and frontier), function as benchmarks for global investors. The correlation between oil prices and these indexes is complex, carrying significance for risk evaluations, investment choices, and the general attitude of the market.

Economic analysts and investors have shown considerable interest in the correlation between the MSCI index and oil prices. A multitude of scholarly investigations have been undertaken to examine the dynamic interplay between oil prices and the MSCI index (Youssef and Mokni, 2019). This study examines the relationship between oil prices and international markets. To accomplish this, prices for West Texas Intermediate (WTI) and Brent were utilized. As market indicators, various indices with distinct market characteristics were selected. MSCI indices divide the world's investable markets into three categories: developed, emerging, and frontier. Within this framework, the research investigates how different regional indices are impacted by changes in oil prices and the nature of their relationship. Oil prices and stock markets may exhibit nonlinear behavior due to global economic and political developments (Wen et al., 2019). The study utilizes nonlinear methodologies to ascertain the presence of a causal connection between oil prices and global markets. This study investigates the extent to which oil prices might provide diversification opportunities and possible returns for a potential investment. Hence, the research aims to offer valuable insights into potential alternative investment strategies that may arise from the conducted investigations. This work makes valuable contributions to the existing knowledge base.

2.LITERATURE REVIEW

Oil prices and stock markets have been found to exhibit a positive association in certain research. Arouri and Fouquau (2009) observed that the stock markets of Qatar, Oman, and the United Arab Emirates saw favorable effects from rises in oil prices, whereas the stock markets of other Gulf Cooperation Council (GCC) nations did not exhibit any response. Mohanty et al. (2011) identified a significant correlation between changes in oil prices and the performance of stock markets in GCC nations, with the exception of Kuwait.

Antonakakis, Chatziantoniou and Filis (2017) identified substantial effects of the futures market for oil on China's stock market between September 1995 and July 2013. In their study, Wen, Bouri, and Cheng (2019) discovered a direct relationship between the stock markets of emerging countries and the pricing of crude oil, indicating a positive association. In their study, Prabheesh, Garg, and Padhan (2020) examined the correlation between oil prices and stock markets in the top 10 net oil-exporting nations. Amidst the COVID-19 epidemic, the DCC-GARCH model unveiled a fluctuating positive association between oil prices and stock markets.

Multiple published studies have revealed a negative relationship between oil prices and stock markets. Dhaoui and Kgraief (2014) found a negative association between the stock markets of seven developed countries and oil prices for the period from January 1991 to September 2013. In their study, Diaz, Molero, and De Gracia (2016) provided evidence that the stock markets of the G7 countries had a negative response to an escalation in oil price volatility. The researchers analyzed data from the period of 1970 to 2014. Arfaoui and Ben Rejeb (2017) found a negative correlation between oil prices and stock prices for the period from 1995 to 2015. Fang, Lu, and Egan (2018) assessed the impact of oil prices on several sectors of the Chinese stock market. The investigation conducted between January 1, 2002, and April 30, 2015, employed the Seemingly Unrelated Regression (SUR) model, which demonstrated that variations in oil prices had separate effects on seven sectors. Rahman and Serletis (2019) established a correlation between oil price shocks and a detrimental effect on the U.S. stock market by analyzing high-frequency data. Bagirov and Mateus (2019) aimed to clarify the difference in volatility between oil prices and European markets. The GARCH (1,1) model was employed to evaluate the impact of crude oil prices on trade of Western European oil and gas companies.

Several studies indicate a lack of association between oil prices and stock markets. Cong et al. (2008) demonstrated that oil price shocks had minimal impact on the majority of Chinese stock market indices. Sehgal and Kapur (2012) conducted a study on the impact of oil price shocks on the stock market in fifteen nations from January 1, 1993, to March 31, 2009. The investigation revealed that fluctuations in oil prices had little impact on the stock market prior to the incident. Zhang (2017) analyzed the impact of oil shocks on six prominent stock markets. The investigation typically determined that oil shocks had a little impact on stock prices. Oil shocks might potentially have a positive impact on stock prices.

The relationship between oil prices and stock markets has frequently been examined in terms of their long-term relationship. Several econometric methodologies have been employed in the existing literature to address this subject within this specific setting. İşcan (2010) discovered that there is no enduring relationship between oil prices and the Turkish stock market throughout the period from December 3, 2001 to December 31, 2009. In a study conducted by Kapusuzoglu (2011), a significant and enduring relationship was found between oil prices and the indices of the Istanbul Stock Exchange. Özmerdivanlı (2014) investigated the relationship between the closing prices of the BIST 100 index and oil prices by analyzing monthly data from January 2003 to February 2014. The Engle-Granger cointegration study demonstrates the existence of a persistent relationship between the variables over a long period of time. Markoulis and Neofytou (2016) conducted a study on the G7 and BRIC nations, analyzing data from 1991 to 2016. The findings of the Johansen cointegration analysis indicate that there is no enduring correlation between stock markets and oil prices in the G7 countries. However, a significant link was observed in Brazil, China, and Russia. Zortuk and Bayrak (2016) investigated the correlation between fluctuations in crude oil prices and stock markets in the G-7 countries from April 2002 to August 2014. In her study, Syzdykova (2018) examined the correlation between oil prices and stock prices in Russia, Kazakhstan, and Ukraine over the period from October 2010 to December 2017. Syzdykova (2018) investigated the correlation between fluctuations in oil prices and stock prices in Russia, Kazakhstan, and Ukraine from October 2010 to 2017. The ARDL approach demonstrated the presence of a cointegrated relationship between oil prices and stock prices. In a study conducted by Mokni (2020), it was shown that there is a changing and unequal connection between oil prices and stock markets in nations that both import and export oil.

Extensive research has shown conflicting results about the relationship between stock markets and oil prices. Le and Chang (2011) examined the influence of fluctuations in oil prices on the stock market during the period spanning from January 1986 to February 2011. Based on the study, Japan's stock market exhibited a favorable reaction to oil price shocks, whilst Malaysia's stock market had a negative response. On the other hand, the stock markets of Singapore and South Korea showed an uncertain or unclear response. In their study, Wang, Wu, and Yang (2013) examined the correlation between stock markets and oil prices in countries that export and import oil. They collected data from many countries and evaluated it over the period of January 1999 to December 2011. The analysis revealed that the stock market's response to fluctuations in oil prices varied depending on several factors. In their study conducted in 2013, Wang, Wu, and Yang examined the correlation between stock markets and oil prices in nations engaged in both oil export and import activities from 1999 to 2011. The investigation disclosed that the stock market's reaction to fluctuations in oil prices differed based on certain criteria. In a study conducted by Arshad and Bashir (2015), the relationship between crude oil and natural gas prices, stock prices, currency rates, and interest rates in Pakistan from 2009 to 2013 was investigated. The study revealed that fluctuations in oil prices had a detrimental effect on the profitability of chemical and textile stocks. Additionally, it was observed that the gas price component had a significant role in influencing the textile business. The stock index returns have a substantial influence on the returns of equities in each sector. Wei et al. (2019) established a durable connection between the Chinese stock market and oil futures prices by employing the Hatemi-J cointegration technique over the period of 2005 to 2017.

Table 1. Direction of causality between oil prices and stock markets

Author(s)	Period	Country/ Group	Method	Relationship
Arouri and Rault (2010)	07.06.2005 – 21.10. 2008 and 1996:01 – 2007:12	GCC	Granger	S ↔ O (Saudi Arabia) O → S (Other GCC ülkeleri)
Hasan and Mahbobi (2013)	21.11.2008 - 19.08.2011	Canada	Toda- Yamamoto	O → S
Özmerdivanlı (2014)	2003:01 – 2014:02	Turkey	Granger	S → O
Akinlo (2014)	1981 - 2011	Nigeria	Granger	O → S
Ghosh and Kanjilal (2016)	02.07.2007 to 29.07.2011	India	Toda Yamamoto	O → S
Çevik, Atakuren and Korkmaz (2018)	01.01.1988 – 27.08.2018	G7	Causality-in-mean, Causality- in- variance	S → O (Brent)
Wen, Bouri and Cheng (2019)	06.04.2001 – 30.09.2016	China	Nonlinear causality	O → S
Peng et al. (2020)	2005.01.06 - 2016. 07.08	China	Linear and nonlinear Granger	S ↔ O (nonlinear Granger) O → S (linear Granger)
Ghedira and Nakhli (2023)	1995:10 – 2021:10	Russia	Granger	O → S (Russia)
Banerjee, Majumdar and Mohammed (2023)	2006 - 2019	United Arab Emirates	Granger	S ↔ O
Akbulaev et al. (2023)	2015:01 – 2022:12	Russia	Granger	S ↔ O
Abakah et. al (2023)	01.06.2005 – 24.09.2018	GCC, OPEC	Hiemstra-Jones and Diks – Panchenko tests	S ↔ O
Ren et. al (2023)	27.01.2014 – 18.09 2020	Europe	Causality-in-Quantiles	S ↔ O (Germany, France)
Raifu (2023)	2011 - 2021	Norway	Time- varying Granger	S ↔ O (daily data) S → O (weekly and monthly data)

Note: O: Oil price, S: Stock exchange

In their study, Ftiti, Guesmi, and Abid (2016) examined the relationship between stock markets and oil prices in G7 countries. The wavelet approach was utilized as the methodology for their inquiry. The investigation's findings suggest that the connection between oil and stock markets is more noticeable in the short and medium time periods, rather than in the long-term. Arshad (2017) sought to examine the relationship between Islamic stock markets and oil prices throughout the period from 2002 to 2016. The study utilized EGARCH and Multifractal Detrended Fluctuation methodologies to determine the simultaneous correlation between volatility in Islamic stock markets and oil. In their study, Joo and Park (2017) analyzed the impact of uncertainty related to stock markets in the United States, Japan, Korea, and Hong Kong, as well as crude oil prices, on the returns seen in these markets. The results obtained from employing the Dynamic Conditional Correlation (DCC) GARCH model indicated that variations in uncertainty have time-varying negative effects on returns during certain time periods.

It is not feasible to establish a definitive correlation between oil prices and stock markets (Hanif, 2020). Table 1 presents a comprehensive summary of research on the causal relationship between oil prices and stock markets. Some studies examining different country groups suggest a causality relationship from stock markets to oil prices (Özmerdivanlı, 2014; Çevik, Atukeren and Korkmaz, 2018). In contrast, some studies suggest causality from oil prices to stock markets (Akinlo, 2014; Ghosh and Kanjilal, 2016; Wen, Bouri and Cheng 2019; Ghedira and Nakhli, 2023). Some studies in the literature have found evidence of bidirectional causality between oil prices and stock markets (Banerjee, Majumdar and Mohammed, 2023; Akbulaev, Muradzada and Hasanov, 2023; Abakah et al., 2023; Ren et al., 2023). The results of research analyzing different nations or country groups have changed based on the data format or particular countries examined (Arouri and Rault, 2010; Peng et al., 2020; Raifu, 2023).

3.DATA AND METHODOLOGY

3.1.Data

MSCI contributes significantly to measuring the performance of international stock markets. These indices are considered crucial factors for investors to assess and expose risks associated with different countries' stock markets. MSCI indices are regularly reviewed and updated, being evaluated and monitored by investors in international portfolio investments for their accuracy in reflecting changes in stock markets. MSCI indices were utilized in this study.

The study investigates the relationship between WTI and Brent oil prices and MSCI global markets. Four different MSCI indices and weekly oil price data were utilized for the analysis. The study consists of 301 observations spanning from January 7, 2018 to October 8, 2023. The MSCI WORLD index represents 23 developed markets, while the MSCI EM (Emerging Markets) covers 27 emerging markets, and MSCI FM (Frontier Markets) includes 27 frontier markets. The MSCI G7 index, on the other hand, comprises 7 developed markets. Among these indices, MSCI WORLD and G7 represent developed markets, MSCI EM represents emerging markets, and FM indices represent frontier market economies. The study's data was retrieved from the website "www.investing.com". All data were analyzed in USD. The natural logarithms of all series employed in the study were analyzed.

The descriptive statistics for the series are shown in Table 2. The standard deviation values indicate that the highest variability is observed in the BRENT and WTI series. Accordingly, the negative skewness values indicate that the distributions of the WOLRD, G7, BRENT, and WTI series are left-skewed. On the other hand, the positive skewness values for the EM and FM series indicate right-skewed distributions. The MSCI index series have playtkurtic distribution based on kurtosis values, but the oil price series exhibit a leptokurtic.

Table 2. Descriptive Statistics

Statistics	**WORLD**	**EM**	**FM**	**G7**	**BRENT**	**WTI**
Mean	7.817	6.987	6.787	7.735	4.231	4.152
Standard Deviation	0.156	0.120	0.111	0.163	0.297	0.322
Skewness	-0.028	0.380	0.276	-0.038	-0.949	-1.037
Kurtosis	1.737	2.435	2.947	1.679	4.455	5.232
Minimum	7.409	6.689	6.481	7.319	3.065	2.829
Maximum	8.081	7.265	7.039	8.009	4.804	4.793

Note: Logarithmic transformations have been applied to the series. The values parentheses indicate p-values.

3.2. Methodology

3.2.1 Brock, Dechert and Scheinkman (1987) Test

The financial series must be stationary in time series analysis. The Brock, Dechert, and Scheinkman (BDS) test is done to determine whether the series is nonlinearity. The test is widely used to financial and economic time series as well as stock market indexes. The test is a test of independence that can be applied to the estimated errors of the time series model. The BDS test statistic (1) is calculated as follows.

$$\mathbf{BDS_t} = \sqrt{\mathbf{T}}\frac{\mathbf{C_{m,T}(\varepsilon) - C_{1,T}(\varepsilon)^m}}{\boldsymbol{\sigma}_{\mathbf{m,T}}(\boldsymbol{\varepsilon})} \quad (1)$$

In the BDS test, which is considered as a nonlinearity test. The correlation dimension $\mathbf{C_{m,T}(\varepsilon)}$ is defined as in equation (2) (Graaff et al., 2001).

$$\mathbf{C_{m,T}(\varepsilon)} = \sum_{t<s} \mathbf{I_\varepsilon(x_t^m, x_s^m)}\left[\frac{\mathbf{2}}{\mathbf{T_m(T_m - 1)}}\right] \quad (2)$$

3.2.2. Sollis (2009) Test

Financial time series, which are analyzed with the assumption that they are linear based on traditional models, may give erroneous results. It has been proposed that the inability to obtain economically meaningful results in studies may be due to the linearity assumption (Pavlidis, et al., 2013).

On the basis of various assumptions and models, nonlinear unit root tests have been created. Kapetanios et al. (2003) employ a nonlinear approach, building on the Exponential Smooth Transition Autoregressive (ESTAR) model as shown below:

$$\Delta \mathbf{y_t} = \boldsymbol{\rho} \mathbf{y_{t-1}}[\mathbf{1} - \mathbf{exp}\,(-\boldsymbol{\gamma}(\mathbf{y_{t-1}^2}))] + \boldsymbol{\varepsilon}_\mathbf{t}, \qquad \boldsymbol{\gamma} \geq \mathbf{0} \quad (3)$$

In Equation (3) $\mathbf{y_t}$ is the time series, and $\boldsymbol{\varepsilon}_\mathbf{t}$ is assumed to be a zero-mean, constant variance, independently and identically distributed series with d = 1. $[\mathbf{1} - \mathbf{exp}\,(-\boldsymbol{\gamma}(\mathbf{y_{t-1}^2}))]$ is the exponential transition function. Sollis (2009) has developed a new test based on the ESTAR model. This approach is tested under the model relying on the nonlinearity of both symmetric and asymmetric ESTAR cases. This model employs both exponential and logistic functions, as illustrated below:

$$\Delta \mathbf{y_t} = \mathbf{G_t}(\boldsymbol{\gamma}_\mathbf{1}, \mathbf{y_{t-1}})[\mathbf{S_t}(\boldsymbol{\gamma}_\mathbf{2}, \mathbf{y_{t-1}})\boldsymbol{\rho}_\mathbf{1} + (\mathbf{1} - \mathbf{S_t}(\boldsymbol{\gamma}_\mathbf{2}, \mathbf{y_{t-1}})\boldsymbol{\rho}_\mathbf{2}]\mathbf{y_{t-1}} + \boldsymbol{\varepsilon}_\mathbf{t} \quad (4)$$

$$\mathbf{G_t}(\boldsymbol{\gamma}_\mathbf{1}, \mathbf{y_{t-1}}) = \mathbf{1} - \mathbf{exp}\,(-\boldsymbol{\gamma}_\mathbf{1}(\mathbf{y_{t-1}^2})) \qquad \boldsymbol{\gamma}_\mathbf{1} \geq \mathbf{0} \quad (5)$$

$$\mathbf{S_t}(\boldsymbol{\gamma}_\mathbf{2}, \mathbf{y_{t-1}}) = [\mathbf{1} + \mathbf{exp}\,(-\boldsymbol{\gamma}_\mathbf{2}\mathbf{y_{t-1}})]^{-1} \qquad \boldsymbol{\gamma}_\mathbf{2} \geq \mathbf{0} \quad (6)$$

Equation (4) can be expanded and rewritten as follows:

$$\Delta \mathbf{y_t} = \mathbf{G_t}(\boldsymbol{\gamma}_\mathbf{1}, \mathbf{y_{t-1}})[\mathbf{S_t}(\boldsymbol{\gamma}_\mathbf{2}, \mathbf{y_{t-1}})\boldsymbol{\rho}_\mathbf{1} + (\mathbf{1} - \mathbf{S_t}(\boldsymbol{\gamma}_\mathbf{2}, \mathbf{y_{t-1}})\boldsymbol{\rho}_\mathbf{2}]\mathbf{y_{t-1}} + \sum_{i=1}^{k} \boldsymbol{\kappa}_\mathbf{i}\, \Delta \mathbf{y_{t-i}} + \boldsymbol{\varepsilon}_\mathbf{t} \quad (7)$$

The Sollis (2009) approach allows testing the null hypothesis of stationary symmetric or asymmetric non-linear ESTAR against the alternative of non-linear ESTAR, which is used as an auxiliary model (equation (8)), in case the null hypothesis against non-linear symmetric ESTAR is rejected. The standard F test can be employed to test the null hypothesis under the assumption ($\mathbf{H_0}: \boldsymbol{\Phi}_\mathbf{1} = \boldsymbol{\Phi}_\mathbf{2} = \mathbf{0}$).

$$\Delta \mathbf{y_t} = \boldsymbol{\Phi}_\mathbf{1}\mathbf{y_{y-1}^3} + \boldsymbol{\Phi}_\mathbf{2}\mathbf{y_{t-1}^4} + \sum_{i=1}^{k} \boldsymbol{\kappa}_\mathbf{i}\, \Delta \mathbf{y_{t-i}} + \boldsymbol{\eta}_\mathbf{i} \quad (8)$$

The test statistic in Sollis (2009) is calculated as in equation (9). Critical values for the test are provided in the study by Sollis (2009).

$$\mathbf{F} = \left(\mathbf{R}\widehat{\boldsymbol{\beta}} - \mathbf{r}\right)' \left[\widehat{\boldsymbol{\sigma}}^2 \mathbf{R} \left\{\sum_t \mathbf{x}_t \mathbf{x}_t'\right\}^{-1} \mathbf{R}'\right]^{-1} (\mathbf{R}\widehat{\boldsymbol{\beta}} - \mathbf{r})/\mathbf{m} \quad (9)$$

3.2.3. Hu and Chen (2016) Test

Hu and Chen (2016) proposed a new unit root test based on the ESTAR process, which is used to examine time series with a nonlinear structure. This test is considered under the following ESTAR (1) model:

$$\Delta \mathbf{y}_t = \boldsymbol{\alpha} \mathbf{y}_{t-1} + \boldsymbol{\gamma} \mathbf{y}_{t-1}[\mathbf{1} - \exp\left(-\boldsymbol{\theta}(\mathbf{y}_{t-1} - \mathbf{c})^2\right)] + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\theta} \geq \mathbf{0} \quad (10)$$

In Equation (10) $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}$, $\boldsymbol{\theta}$ and $\mathbf{c}$ represent unknown parameters. The auxiliary regression equation obtained using the Taylor expansion for the Hu and Chen (2016) test is expressed as follows:

$$\Delta \mathbf{y}_t = \boldsymbol{\beta}_1 \mathbf{y}_{t-1} + \boldsymbol{\beta}_2 \mathbf{y}_{t-1}^2 + \boldsymbol{\beta}_3 \mathbf{y}_{t-1}^3 + \mathbf{u}_t \quad (11)$$

In equation (11), $\boldsymbol{\beta}_3$ is less than zero. $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$ an take positive or negative values depending on the parameter c. This approach is tested under the following null hypothesis:

$\mathbf{H}_0\colon \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 = \boldsymbol{\beta}_3 = \mathbf{0}$

The approach by Hu and Chen (2016) is applied based on the modified Wald test statistic as follows:

$$\boldsymbol{\tau} = \left(\widehat{\boldsymbol{\beta}}_1 - \frac{\widehat{\boldsymbol{\beta}}_3 \widehat{\boldsymbol{\upsilon}}_{13}}{\widehat{\boldsymbol{\upsilon}}_{33}} \quad \widehat{\boldsymbol{\beta}}_2 - \frac{\widehat{\boldsymbol{\beta}}_3 \widehat{\boldsymbol{\upsilon}}_{23}}{\widehat{\boldsymbol{\upsilon}}_{33}}\right) \mathbf{x} \begin{pmatrix} \widehat{\boldsymbol{\upsilon}}_{11} - \frac{\widehat{\boldsymbol{\upsilon}}_{13}^2}{\widehat{\boldsymbol{\upsilon}}_{33}} & \widehat{\boldsymbol{\upsilon}}_{12} - \frac{\widehat{\boldsymbol{\upsilon}}_{13}\widehat{\boldsymbol{\upsilon}}_{23}}{\widehat{\boldsymbol{\upsilon}}_{33}} \\ \widehat{\boldsymbol{\upsilon}}_{12} - \frac{\widehat{\boldsymbol{\upsilon}}_{13}\widehat{\boldsymbol{\upsilon}}_{23}}{\widehat{\boldsymbol{\upsilon}}_{33}} & \widehat{\boldsymbol{\upsilon}}_{22} - \frac{\widehat{\boldsymbol{\upsilon}}_{23}^2}{\widehat{\boldsymbol{\upsilon}}_{33}} \end{pmatrix}^{-1} \mathbf{x} \left(\widehat{\boldsymbol{\beta}}_1 - \frac{\widehat{\boldsymbol{\beta}}_3 \widehat{\boldsymbol{\upsilon}}_{13}}{\widehat{\boldsymbol{\upsilon}}_{33}} \quad \widehat{\boldsymbol{\beta}}_2 - \frac{\widehat{\boldsymbol{\beta}}_3 \widehat{\boldsymbol{\upsilon}}_{23}}{\widehat{\boldsymbol{\upsilon}}_{33}}\right)' + \mathbf{1}_{\widehat{\boldsymbol{\beta}}_3 < 0} \frac{\widehat{\boldsymbol{\beta}}_3}{\widehat{\boldsymbol{\upsilon}}_{33}} \quad (12)$$

The test statistic is computed using the test statistic derived from the Hessian matrix, as shown in the following equation (12). When we formulate the test statistic in a simplified form, it is obtained as follows in equation (13). The $\boldsymbol{\tau}_3^2$ in equation (13) is the square of the t-statistic used for $\boldsymbol{\beta}_3 = \mathbf{0}$. The critical values for the Hu and Chen (2016) approach are provided in their study.

$$\boldsymbol{\tau} = \boldsymbol{\tau}_1^2 + \mathbf{1}_{\boldsymbol{\tau}_3 < 0} \boldsymbol{\tau}_3^2 \quad (13)$$

3.2.4. Diks and Panchenko (2006) nonlinear causality test

The Granger causality test does not account for the nonlinear relationship between variables. Hiemstra and Jones (1994) aimed to analysis the test with a nonlinear method. Diks and Panchenko proposed a new test and this method aimed to solve the consistency problem in Hiemstra and Jones (1994) study (Diks and Panchenko, 2005).

The test statistic obtained using the joint probability density function $\mathbf{f}_{X,Y,Z}(\mathbf{X}_i, \mathbf{Y}_i, \mathbf{Z}_i)$ is calculated as shown in equation (14).

$$\mathbf{T}_n(\boldsymbol{\varepsilon}) = \frac{(\mathbf{n}-\mathbf{1})}{\mathbf{n}(\mathbf{n}-\mathbf{2})} \sum_i \left(\hat{\mathbf{f}}_{X,Y,Z}(\mathbf{X}_i, \mathbf{Y}_i, \mathbf{Z}_i)\, \hat{\mathbf{f}}_Y(\mathbf{Y}_i) - \hat{\mathbf{f}}_{X,Y}(\mathbf{X}_i, \mathbf{Y}_i) \hat{\mathbf{f}}_{Y,Z}(\mathbf{Y}_i, \mathbf{Z}_i)\right) \quad (14)$$

The bandwidth values are consistent estimators obtained for an appropriate sequence $\boldsymbol{\varepsilon}_n$. The expression states that, for a constant parameter C and $\boldsymbol{\beta} \in \left(\frac{1}{4}, \frac{1}{3}\right)$, the test statistic is asymptotically normally distributed.

Diks and Panchenko (2006) argued that the definition and functioning of Granger causality in Hiemstra and Jones (1994) has not been fully revealed. Diks and Panchenko (2006) developed a nonlinear method for stationary variables to find a solution to the problem of excessive rejection of the null hypohtesis and to ensure consistency (Wang and Wu, 2012: 2290). When applying the nonlinear causality test, first of all, it is necessary to chech whether the series is nonlinear. This method states that the VAR model should be estimated first in order to eliminite linear dependence. Nonlinear causality analysis should be performed by estimating the error terms of the VAR model established with the appropriate lag length. The filtered error terms of the VAR model are important in terms of revealing the nonlinear structure.

4.FINDINGS

In the study, the stationarity of the series is tested through unit root tests. The relationship between MSCI global equity market indices and crude oil and Brent oil prices was analyzed using the nonlinear causality analysis. In this context, it is important for the series to be linear or not for the analysis. The null hypothesis is based on the assumption that the series is linear. According to the findings of the BDS linearity test shown in Table 3, the null hypothesis that all series are linear at the 1% significance level is rejected. The results indicate that all series are nonlinear.

Table 3. Results of BDS Test

Series	m=2	m=3	m=4	m=5	m=6
WORLD	0.179* (0.000)	0.303* (0.000)	0.388* (0.000)	0.444* (0.000)	0.480* (0.000)
EM	0.174* (0.000)	0.296* (0.000)	0.379* (0.000)	0.433* (0.000)	0.467* (0.000)
FM	0.185* (0.000)	0.313* (0.000)	0.398* (0.000)	0.454* (0.000)	0.489* (0.000)
G7	0.180* (0.000)	0.305* (0.000)	0.390* (0.000)	0.447* (0.000)	0.485* (0.000)
WTI	0.177* (0.000)	0.299* (0.000)	0.382* (0.000)	0.436* (0.000)	0.469* (0.000)
BRENT	0.178* (0.000)	0.301* (0.000)	0.386* (0.000)	0.441* (0.000)	0.476* (0.000)

Note: * denotes 1% significant level. The values in parentheses represent the p-values.

The results of a linear unit root test are presented in Table 4. The ADF test results indicate that the series could not reject the presence of a unit root at the level. When the first difference of all series is taken, the null hypothesis, which suggests the presence of a unit root at the 1% significance level, is rejected. As a result, differencing the series once has made them stationary.

Table 4. Results of ADF Unit Root Test

Series	Level		First Difference	
	statistics	**prob**	**statistics**	**prob**
WORLD	-2.593	0.284	-18.806*	0.000
EM	-1.853	0.676	-16.793*	0.000
FM	-2.139	0.522	-13.728*	0.000
G7	-2.626	0.269	-19.085*	0.000
WTI	-2.353	0.404	-14.881*	0.000
BRENT	-2.019	0.588	-16.372*	0.000

Note: * denotes 1% significant level.

The Sollis (2009) and Hu and Chen (2016) approaches were used for the nonlinear unit root test. Table 5 presents the test statistic values for both approaches. According to both methods, the level values of the variables exhibit a unit root. However, when taking the first difference of the variables, the presence of a unit root is rejected at the 1% significance level for all variables (except WTI at 5% level). As a result, it is noticed that all variables become stationary when the first difference is taken.

Table 5. Results of Sollis (2009) Nonlinear Unit Root Test

Series	Level		First Difference	
	Sollis (2009)	Hu and Chen (2016)	Sollis (2009)	Hu and Chen (2016)
WORLD	1.165	3.694	9.299***	353.592***
EM	1.657	6.388	8.111***	293.740***

FM	1.757	8.552	62.077***	197.067***
G7	1.143	3.469	12.135***	362.243***
WTI	1.140	3.822	3.809**	236.367***
BRENT	0.894	3.039	1.912*	271.279***

Note: ***,**,* significance at the level 1%, 5% and 10%, respectively. The appropriate delay lengths were determined according to the Bayesian Information Criterion (BIC). According to the Sollis (2009) test, the values of 1.837, 2.505, and 4.241 are significant at the 10%, 5%, and 1% levels, respectively. For the Hu and Chen (2016) test, the values of 9.49, 11.22, and 15.12 are significant at the 10%, 5%, and 1% levels, respectively.

Table 6 displays the findings of the linear Granger causality between WTI oil prices and MSCI indices. The analysis indicates a unidirectional causality between MSCI indices and WTI oil prices. According to these results, MSCI indices are found to be the linear Granger cause of WTI. The findings of this study are consistent with those of Özmerdivanlı (2014) who employed a similar method. However, there is no linear causality found from WTI to MSCI indices. Similarly, the linear Granger causality test results between Brent crude oil prices and MSCI stock indices, as shown in Table 6, indicate a unidirectional causality relationship. In this case, MSCI indices are found to be the linear Granger cause of Brent crude oil prices. The analysis results do not show Brent as the linear cause of the indices.

Table 6. Results of Linear Granger Causality

Causality	t statistics	p value	Causality	t statistics	p value
WORLD → BRENT	2.909**	0.004	WORLD → WTI	3.832**	0.005
BRENT → WORLD	0.738	0.658	WTI → WORLD	0.741	0.565
EM → BRENT	4.145*	0.043	EM → WTI	2.821*	0.025
BRENT → EM	0.160	0.690	WTI → EM	0.389	0.817
FM → BRENT	6.388*	0.012	FM → WTI	6.352**	0.000
BRENT → FM	0.475	0.491	WTI → FM	0.179	0.949
G7 → BRENT	2.943*	0.004	G7 → WTI	3.787**	0.005
BRENT → G7	0.812	0.593	WTI → G7	0.912	0.457

Note: **,* significance at the level 1% and 5%, respectively.

Table 7 presents the results of the nonlinear Granger causality analysis between WTI crude oil prices and MSCI indices with different lags. The results suggest at least a unidirectional nonlinear causality at the 10% significance level between WTI and MSCI WORLD, FM, and G7 indices.

Table 7. Results of nonlinear causality test (WTI)

Causality	Lx=Ly=1	Lx=Ly=2	Lx=Ly=3	Lx=Ly=4	Lx=Ly=5
WORLD → WTI	1.301* (0.097)	2.176** (0.015)	3.362*** (0.000)	2.910*** (0.002)	2.240** (0.013)
WTI → WORLD	0.706 (0.240)	0.792 (0.214)	0.782 (0.217)	0.842 (0.199)	1.239 (0.108)
EM → WTI	1.306* (0.096)	1.081 (0.139)	2.278** (0.011)	3.144*** (0.001)	2.729*** (0.003)
WTI → EM	1.394* (0.082)	0.846 (0.199)	1.639* (0.051)	1.334* (0.091)	1.396* (0.081)
FM → WTI	1.845** (0.033)	1.314* (0.094)	1.781** (0.037)	1.993** (0.023)	2.189** (0.014)
WTI → FM	0.884 (0.188)	0.172 (0.432)	-0.544 (0.707)	-0.590 (0.722)	-0.684 (0.753)
G7 → WTI	1.340* (0.090)	2.168** (0.015)	3.469*** (0.000)	3.079*** (0.001)	2.489*** (0.006)
WTI → G7	0.763 (0.223)	0.872 (0.192)	0.995 (0.159)	1.025 (0.153)	1.258 (0.104)

Note: The bandwidth is set to Ɛ=1.5. ***,**,* significance at the level 1%, 5% and 10%, respectively. The values in parentheses represent the p-values.

Table 8 presents the results of the nonlinear Granger causality relationship between Brent oil prices and MSCI indice for different lags. Bidirectional nonlinear causality between MSCI WORLD and BRENT has been found to be valid for three lags at least a significance level of 5%. For MSCI EM and BRENT, bidirectional nonlinear causality is observed for at least the significance level of 10%, except for one lag (Lx=Ly=2). According to the conclusion, MSCI FM is the nonlinear cause of BRENT. For MSCI G7 and BRENT, bidirectional nonlinear causality seems to exist for two lags at least significance level of 10%.

Table 8. Results of nonlinear causality test (Brent)

Causality	Lx=Ly=1	Lx=Ly=2	Lx=Ly=3	Lx=Ly=4	Lx=Ly=5
WORLD → BRENT	2.178** (0.015)	2.636*** (0.004)	3.069*** (0.001)	2.808*** (0.002)	2.639*** (0.004)
BRENT → WORLD	1.107 (0.134)	1.240 (0.108)	2.225** (0.013)	2.649*** (0.004)	2.796*** (0.003)
EM → BRENT	1.744** (0.041)	1.248 (0.106)	2.118** (0.017)	2.524*** (0.006)	2.124** (0.017)
BRENT → EM	1.871** (0.031)	0.855 (0.196)	1.294* (0.098)	1.799** (0.036)	1.516* (0.065)
FM → BRENT	1.974** (0.024)	1.571* (0.058)	1.934** (0.027)	2.005** (0.022)	2.065** (0.019)
BRENT → MSCI	1.036 (0.150)	0.355 (0.369)	-0.204 (0.581)	0.172 (0.432)	0.436 (0.331)
G7 → BRENT	2.089** (0.018)	2.444*** (0.007)	3.152*** (0.001)	2.820*** (0.002)	2.673*** (0.004)
BRENT → G7	1.237 (0.108)	1.524* (0.064)	2.507*** (0.006)	2.712*** (0.003)	2.846*** (0.002)

Note: The bandwidth is set to Ɛ=1.5. ***,**,* significance at the level 1%, 5% and 10%, respectively. The values in parentheses represent the p-values.

5.CONCLUSION and DISCUSSION

This study examines the relationship between oil prices and worldwide stock markets from January 7, 2018, to October 8, 2023. Studies in the literature have produced varied findings when investigating the relationship between oil prices and stock markets across different nations and country groups across different time periods. This study investigates the non-linear relationship between oil prices and stock markets. Different indicators are included in the study to depict various stages of growth. The MSCI use the WORLD, EM, FM, and G7 indexes to depict developed, developing, and frontier economies, respectively.

Two distinct nonlinear unit root tests have been utilized in the application. The stationary nonlinear series were subjected to the application of the nonlinear causality test proposed by Diks and Panchenko (2006). The findings in this study, based on the applied approach, are consistent with the results of Peng et al. (2020), Abakah et al. (2023), and Ren et al. (2023) studies that employed similar methods. The causality test showed that there is a one-way nonlinear relationship between WTI crude oil prices and the MSCI WORLD, FM, and G7 indices. The causal relationship illustrates that stock market indices may exert a non-linear influence on oil prices. The relationship between the MSCI EM index and oil prices is characterized by nonlinear bidirectional causality. Several studies in the literature (Çevik et al., 2018; Raifu, 2023) support the direction of causality from indices to oil prices. Nonlinear bidirectional causality, except for a lag of one period (Lx=Ly=2), is found to be significant at the 10% level between WTI and MSCI EM index. There is a reciprocal relationship between the pricing of Brent crude oil and the MSCI WORLD and EM indices. There may be a reciprocal relationship between the expansion of stock markets and fluctuations in oil prices. The findings indicate that the MSCI FM index is a significant nonlinear factor influencing BRENT. The results of the research indicate that it could be prudent to incorporate non-linear causal links between gasoline prices and indices when determining portfolio allocations.

The study's conclusions can be beneficial for investors, researchers, and regulators. The study's use of indexes reflecting stock markets with varying degrees of global development can give investors in different nations with valuable insights. Firstly, investors should develop their portfolio management and risk hedging strategies with the nonlinear link between oil prices and stock markets in mind. It would be wise for them to incorporate nonlinearity from the beginning into their models and plans. Investors can limit risk by paying attention to the direction of the link between stock markets and oil prices during the investment process. Furthermore, in light of the bidirectional non-linear causation that has been discovered between oil prices and MSCI indexes, it is possible to include portfolio diversification strategies. In conjunction with risk mitigation, this strategy has the potential to improve portfolio performance. By incorporating non-linear techniques into their risk assessment models, financial institutions can enhance the precision of their forecasts and assessments on the correlations between MSCI indexes and oil prices. Policymakers should be mindful of the fluctuations in oil prices. In the event that oil prices increase or decrease, it is crucial for them to implement procedures that account for nonlinear relationships. Given the discernible asymmetrical connections, it is prudent for policymakers and investors to diligently follow worldwide political and economic affairs, as these aspects possess the capacity to have an impact on the interplay between oil prices and MSCI indexes. The correlation between energy reliance and financial markets is exemplified by the link between oil prices and indices. The transition to alternate energy sources and the reduction of energy reliance should be the focus of national policy considerations.

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