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Nonlinear Causal Relationship between Oil Prices, Global Uncertainty and Investor Sentiments

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ABSTRACT

In recent years, as a result of developments in global markets, the financial decision-making mechanism of individuals has become one of the most debated topics. In the literature, despite the fact that linear relationship between energy market and investor sentiment is investigated, usually traditional tests are applied. Further, uncertainty conditions at the global level are not taken into account within the frame of markets and sentiment relations. The relationship between oil prices and investor sentiment is outstanding for asset allocation and portfolio risk management under conditions of uncertainty. This research paper examines the connection between energy market, global uncertainty and investor sentiment using monthly data between 2004 and 2024. In the analysis, firstly, it is examined that whether the series are linear or not employing linearity test. Then, quantile causality test is applied to the series that are determined to be non-linear. Empirical findings provide that investor sentiment cause oil prices while oil prices cause global uncertainty. In addition, global uncertainty and investor sentiment have a mutual causal relationship. Analysis results revealed that investor sentiment significantly affects the energy markets, and there is a strong association between global uncertainty and investment sentiment.

Keywords: Energy Markets, Global Uncertainty, Sentiment Analysis, Quantile
JEL Classifications: C51, G41, Q41

1. INTRODUCTION

The increasing complexity of uncertainty conditions all around the world and their impacts on economic activities necessitate further research of the relationships between markets and sentiment. Investors make their investment decisions not only based on information in stock markets but also on information valid in commodity markets. Examining the interaction between energy market and sentiment is quite significant in regards to asset allocation and portfolio risk management (Kumar, 2019: 41-42; Li et al., 2019: 1-2).

In the studies, it is indicated that oil price changes affect stock prices through the investor sentiment mechanism. Investors follow both energy and stock markets movements simultaneously, as the financialization of oil markets provides a substitution mechanism between oil and stock markets. Investors believe that an increase in oil prices will negatively affect stock prices by causing a decrease in exchange rates and increasing inflation (Hatemi et al., 2016: 1589; Kumar, 2019: 41). In this regard, psychological factors, investors "believes, besides financial factors come to the fore in the decision-making process. It is determined that investors affect price formation in markets considering their emotions in the financial investment decision-making process. Statman (1999) and Baker and Wurgler (2006) argued that investors" psychological conditions such as confidence, perception, perspective, and information processing have a significant impact on prices. In the finance literature, the notion of sentiment is associated with emotions; investor sentiment is mostly defined as fear or risk aversion. It refers to the person forming his/her expectations with overly optimistic or pessimistic feelings.

Further, in recent years, the interaction between investment decisions; therefore, sentiment and energy market has become more significant. Fluctuations in oil prices have direct impacts on inflation, economic growth and stock market performance (Filis, 2010: 879). On the other hand, changes in oil prices affect the economic performance of countries differently depending on the degree of oil dependency, the heterogeneity of their economic structures, the level of development of economic and financial markets and their integration with the world economy (Narayan et al., 2014: 137-138). In particular, factors such as geopolitical events, uncertainty, market speculation, investors' attention and fears, etc. have a role in the formation of oil prices, unlike other commodity prices (Ajmi et al., 2014: 2167-2169). The main reasons for the change in the relationship between oil prices and investor sentiment over time are implied as the economic development levels of countries, their shares in the global commodity market, demand conditions and the change in risk appetite and sensitivity of financial investors over time (Kilian and Park, 2009; Frankel, 2014; He et al., 2019; Jammazi et al., 2017; Ji et al., 2019).

This research study aims to investigate the interaction with oil prices, global uncertainty and investment sentiment during the period of January 2004 and December 2024. Google Trends search volume index data is employed to measure investment sentiment in energy market. This study make contribution to the literature by examining the association between energy market and sentiment taking into account the uncertainty conditions using current data and applying quantile causality analysis, unlike traditional methods. The remainder of the paper proceeds as follows. The literature related to variables is evaluated in Section 2. And data, methodology and empirical findings are presented in Section 3. Final section consists of conclusion.

2. LITERATURE REVIEW

There are various views in the literature on the relationship and direction between oil prices, global uncertainty and investor sentiment. The interaction between oil prices, uncertainty and investor sentiment is described from an extensive perspective. Particularly, in recent studies, global, economic and policy uncertainty indicators are focused and the connection between the energy market and investors' interest in the energy market is investigated more comprehensively.

In the literature review, it is concluded that there is time varying volatility in both the oil market and the stock market. Fluctuations in oil prices can lead to large changes in stock prices. And this creates uncertainty in the stock market and profit opportunities over time. Investors interested in the performance of stock markets may also exhibit time-varying volatility expectations and emotions that react differently over time. These characteristics point to a time-varying relationship between oil price and investor sentiment (Filis et al., 2011; Caporale et al., 2015).

If the empirical findings of substantial recent studies emphasizing the relationship between oil price formation and investor sentiment are evaluated: Li et al. (2015) examined the relationship between investor sentiment and crude oil prices during the period 2004-2014. They applied the Google search volume index to represent investor attention. In the study, the causality between investor attention and crude oil price is analysed. The results demonstrated that the index improves the crude oil price forecasting accuracy. Qadan and Nama (2018) analysed that behavioural factors such as investor sentiment predict movements in oil prices between 1986 and 2016. As a result of parametric and non-parametric analyses, it is found that investor sentiment has a significant effect on oil prices. Volatility in sentiment indices explain volatility in oil prices. It is also concluded that oil shocks attract the attention of individual investors and that volatility can be predicted to increase in the following trading days with the increasing number of searches. Le and Luong (2022) studied the interaction between oil price shocks; investor sentiment and stock market returns from 2010 to 2020 in the US and Vietnam time-varying parameter vector autoregression (TVP-VAR). The researchers found that oil price and sentiment are net transmitters of shocks in the US whereas in Vietnam, investor sentiment is the principal net transmitter of shocks.

Also, Zhao et al. (2023) aimed to propose a hybrid model using Google Trends as a new indicator to predict changes in oil stocks using ARDL and SVR models. The findings indicate that Google Trends indicator is an effective tool to predict changes in oil stocks. Audi et al. (2025) searched for the relationship between fluctuations in oil prices and stock market performance in Europe period 1991-2023. The study emphasized that how tendencies in energy market impact the stock markets. The researchers conduct the combine methodology of ordinary least squares and quantile regression. Findings suggested that rapid oil price changes caused different levels of sensitivity in the stock market. Li (2025) examined the effects of global supply chain pressures and oil price shocks on investor sentiment in U.S. between the period of 1998-2023 using a nonlinear autoregressive distributed lag model. In the study, long-run estimates stated that investor sentiment is affected negatively by positive global supply chain pressures shocks. Both positive and negative oil price shocks increase the investor sentiment. The negative price shocks carry out a stronger effect on investor sentiment than positive shocks.

In the literature, studies examining uncertainty and investor sentiment are relatively limited. Studies addressing the connection between uncertainty and sentiment emphasize the impacts of uncertainty conditions on the economy and the importance of investor sentiment in restoring stability in financial markets. Shahzad et al. (2017) searched the relationship between economic uncertainty, bullish and bearish investor sentiments from 1996 to 2016. They employed nonparametric causality in quantiles. Considering the causality test results, it is stated that investor sentiment has an impact on the mean and variance of commodities returns which is also more profound compared to economic policy uncertainty. Sakariyahu et al. (2024) investigated the interaction between uncertainty and sentiment factors between 2018 and 2023. The empirical findings indicate that economic and political uncertainty factors significantly drive investors' interest in the market; therefore, the asset prices also affect. Anastasiou et al. (2025) analysed the connection between investor sentiment and oil prices taking into account the developments in global uncertainty in European Union from January 1998 to March 2023. In the study, it is stated that increasing uncertainty conditions around the world affect investors' behaviours, leading to changes in investment decisions and market sentiment. Obadi and Korcek (2024) studied the association between crude oil price and geopolitical events in 2000-2023 using ARDL approach. The empirical findings indicated that there is both long- and short-term link between crude oil price and geopolitical events.

3. DATA, METHODOLOGY AND EMPIRICAL RESULTS

This research study investigates the interaction between oil prices, global uncertainty and investor sentiment all around the world. In this part of the study, firstly the theoretical framework of the data set and analysis method are examined. Next, the empirical findings obtained as a result of the analysis are discussed.

3.1. Data

In the study, it is aimed to examine the relationship between Brent oil, political uncertainty and investor sentiment. applying causality analysis. In the analysis, Brent oil prices, global economic policy uncertainty index and Google Trends search volume index data, which provides data on Google searches obtained from Google Trends tool as a proxy for investor sentiment, are used. The data covers the period from January 2004 to December 2024, selected based on data availability.

Investors' expectations and psychological conditions regarding the market are expressed through Google Trends data, considering the relevant literature. In particular, there are quite significant reasons why Google Trends Search volume data, which has been frequently used in the fields of economics and finance in recent years, is used as a measure of investor sentiment in this study. First of all, since Google is the main search website in the world and provides data that is successfully used as an estimator of economic indicators, Google is generally preferred in the analyses of studies in the literature rather than other search engines (Gomes and Taamouti, 2016). Considering the previous related studies, it is found that Google data can directly measure the investor sentiment that can replace other indirect measures such as turnover, excess returns, news or advertising expenditures (Howard and Sheth, 1969; Da et al., 2011).

The dataset used in the study, their descriptions and information about the sources are shown in Table 1 below.

3.2. Methodology

In the study, after determining the data set and modelling the relationship between the energy market, global uncertainty and investor sentiment, the stationarity levels of the variables are examined. The Augmented Dickey-Fuller (ADF) developed by Dickey and Fuller (1981) and the unit root tests developed by Phillips-Perron (PP) (1988) are used. Then, the linearity structures of the series belonging to the variables are examined. Based on the test results, quantile causality tests are applied to the series determined to be non-linear.

Table 1: Variables and the explanations

Variables	Explanation	Source
brent	Brent Oil prices	Bloomberg
unc	Global economic policy uncertainty index	Economic Policy Uncertainty
google	Google trends search volume for Brent oil worldwide	Google Trends

Table 2: Unit root test results at level

Variables	ADF (c+t)	PP (c+t)
Brent	−3.4485 (0.0474)**	−3.1505 (0.0971)*
Unc	−5.2846 (0.0001)***	−4.9439 (0.0003)***
Google	−4.0571 (0.0082)***	−4.0571 (0.0082)***

In unit root tests, the stationarity levels of the series are obtained within the framework of models without constants and trends, with constants and with constants and trends. In the table, test statistics of the unit root test of the variables are given. The expressions in parentheses indicate the probability values. Based on the *P* values, * denotes significant at the 10%; ** significant at the 5% and *** significant at the 1%. (c+t) stands for the probability values with constant and trend

3.2.1. Unit root tests

The null hypothesis of ADF unit root test states that the series is stationary, against the alternative hypothesis that it has a unit root. If the probability value obtained as a result of the test is <0.05, the null hypothesis that the series contains a unit root is rejected. In the ADF unit root test, the stationarity levels of the series are obtained within the framework of the following models (without constant and trend, constant model and constant and trend) (Dickey and Fuller, 1981:1057-1072). Δ in the model indicates the difference operator, μ is the constant and ε_t is the error term.

$$\Delta Y_t = \delta Y_{t-1} + \sum_{j=1}^{p} \varkappa_j \Delta Y_{t-j} + \varepsilon_t \quad (1)$$

$$\Delta Y_t = \mu + \delta Y_{t-1} + \sum_{j=1}^{p} \varkappa_j \Delta Y_{t-j} + \varepsilon_t \quad (2)$$

$$\Delta Y_t = \mu + \mathrm{B}T + \delta Y_{t-1} + \sum_{j=1}^{p} \varkappa_j \Delta Y_{t-j} \quad (3)$$

The Dickey-Fuller test assumes that the error terms are independently and identically distributed. To be able to use this method, there should be no correlation and heteroscedasticity problems between the error terms. In the stationarity analysis, as an alternative, the PP test can be applied to eliminate the problems in the ADF. Phillips and Perron (1988) presented a nonparametric test in which the error terms are corrected.

The PP test also includes the same hypotheses as the ADF. The null hypothesis of the test states that there is a unit root in the series, and the alternative hypothesis states that the series is stationary. The PP test is also performed using three models, as in the ADF test: with constant, with constant and trend, and without constant and trend. The basic model for the PP test is as follows:

Table 3: Lag order selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−504.2163	NA	0.012828	4.157511	4.200509	4.174828
1	241.5300	1467.042	**0.0000306***	**−1.881393***	**−1.709401***	**−1.812124***
2	249.3928	15.27442	0.0000309	−1.872072	−1.571086	−1.750851
3	258.6246	**17.70704***	0.0000308	−1.873972	−1.443993	−1.700800
4	263.1665	8.599845	0.0000320	−1.837431	−1.278457	−1.612307
5	266.1082	5.497588	0.0000336	−1.787772	−1.099805	−1.510697
6	270.8350	8.717369	0.0000348	−1.752746	−0.935784	−1.423719
7	274.0374	5.827282	0.0000365	−1.705224	−0.759269	−1.324246
8	276.7668	4.899586	0.0000385	−1.653826	−0.578877	−1.220896

Notes: * indicates lag order selected by the criterion. LR stands for sequential modified LR test statistic, FPE means Final prediction error, AIC is Akaike information criterion, SC represents Schwarz information criterion and HQ indicates Hannan-Quinn information criterion. The majority of information criterias suggested that optimal lag length is 1. In the analysis, VAR models are applied considering lag length is 1.

Table 4: BDS test results

Dimension	Brent	Unc	Google
m=2	0.0000***	0.0002***	0.0005***
m=3	0.0000***	0.0055***	0.0003***
m=4	0.0000***	0.0096***	0.0003***
m=5	0.0000***	0.0148**	0.0003***
m=6	0.0000***	0.0378**	0.0006***

In the table, m refers the dimensions for BDS test and the values are the probability values obtained from the test. *** values are 1% significance level. *** states that the null hypothesis is rejected and the residuals do not have independent and identical distributions indicates that the series or model has a non-linear structure

$$\Delta y_t = \alpha y_{t-1} + x_t{'}\delta + \varepsilon_t \quad (4)$$

In the equation, when $\alpha = \rho - 1$, x_t indicates the constant or constant and trend.

3.2.2. Linearity analysis: BDS test

The BDS test, developed by Brock et al. (1996), detects nonlinear dependence in financial time series. The most important feature of this test is to prevent incorrect model selection in series that do not have linearity. In other words, the BDS test is applied against various possible deviations from independence, including linear and nonlinear dependence (Brock et al., 1996).

This method tests that the status of whether the residuals are independently and identically distributed (i.i.d.). The null hypothesis of the test is based on that the variables or the residuals of the estimated models have independent and identical distributions. Thus, the result of that the residuals do not have independent and identical distributions indicates that the series or model has a non-linear structure. In the BDS analysis, the correlation integral expressed below is used as the test statistic:

$$Cm,n\ (\varepsilon) = 1\ (n\ 2)\ \Sigma\,\Sigma\ I\ 1\leq s \quad (5)$$

In the equation, m stands for the fitting size, n for the number of observations, ε for the maximum difference between pairs of observations, and x for the residuals of the filtered model or the data series.

3.2.3. Quantile granger causality analysis

In the study, nonparametric quantile causality analysis developed by Balcılar et al. (2017) is conducted to investigate the nonparametric causality between oil prices, global uncertainty and investor sentiment, based on the methods in the studies of Nishiyama et al. (2011) and Jeong et al. (2012). There are many reasons for using this test in the analysis. Firstly, it is a new method to evaluate nonlinear causality between variables. Nonlinear causality between variables is investigated between different quantiles. Thus, the classical Granger causality test is expanded. In addition, quantile tests have higher performance and ability to explain the relationship compared to other tests. This test presents more reliable results for extreme values in the series. Also, the test is preferred if there are outliers in the data set (Hamadou et al., 2024).

In quantile causality analysis, Jeong et al. (2012) used the null hypothesis that the independent variable x_t is not the Granger cause of the dependent variable y_t with respect to the lag vector $\{y_{t-1},\ldots, y_{t-p}, x_{t-1},\ldots, x_{t-p}\}$ in the θ^{th} quantile and the alternative hypothesis that it is the cause are as follows:

$$H_0=\theta_0(y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p})=\theta_0(y_t|y_{t-1},\ldots,y_{t-p}) \quad (6)$$

$$H_A=\theta_0(y_t|y_{t-1},\ldots,y_{t-p},x_{t-1},\ldots,x_{t-p})\neq\theta_0(y_t|y_{t-1},\ldots,y_{t-p}) \quad (7)$$

$\theta 0(yt|\cdot)$ takes values between 0 and 1 depending on the t value and represents the θth quantile of the y_t variable. Since the causality relationship between oil price, global uncertainty and sentiment is examined bidirectionally in this study, the y and x values also change accordingly. While applying the quantile causality test to the models established in the analysis of the study, the appropriate lag lengths of the models are obtained through VAR analysis.

The main reason for applying the quantile causality test as an analysis method is that, unlike standard causality tests, it does not only take into consideration the causality in the mean. In other words, the quantile causality test also examines the causality in the variance. There are two prerequisites for the application of this method: the series of the variables must be stationary and the relationship between the series must be nonlinear (Balcılar et al., 2017: 151).

3.3. Empirical Results

In the empirical analysis of the study, firstly, the natural logarithm of the series is taken. Then, the stationarity levels of the series are investigated. After determining the level at which the variables are stationary, optimal lag lengths are examined through VAR analysis in the models. After that, the BDS test developed by Brock et al. (1996) is performed to detect non-linear structures in the series.

Table 5: Results of quantile causality test between oil prices-global uncertainty-investor sentiment

Quantiles	Unc ≠> brent	Google≠>brent	Brent≠>google	Unc≠>google	Brent ≠> unc	Google≠>unc
θ=0.1	0.2721	0.6701	0.7648	0.2416	0.5591	0.3161
θ=0.2	0.4040	0.0404**	0.8515	0.8275	0.0632*	0.0021***
θ=0.3	0.2894	0.0785*	0.7893	0.9105	0.0491**	0.0008***
θ=0.4	0.1892	0.0724*	0.3252	0.6783	0.0758*	0.0005***
θ=0.5	0.1886	0.0572*	0.6776	0.1937	0.0357**	0.0115**
θ=0.6	0.2785	0.0472**	0.5277	0.0539*	0.0646*	0.0011***
θ=0.7	0.7878	0.3420	0.6486	0.0344**	0.2732	0.0186**
θ=0.8	0.8124	0.7817	0.6683	0.0538*	0.3088	0.0121**
θ=0.9	0.9850	0.9541	0.8751	0.7129	0.8004	0.5307

In the table, θ indicates quantile values. The values are the probability values obtained for the χ^2 exclusion test in the nonparametric quantile causality test results. ***, ** and * values are 1%, 5% and 10% significance levels, respectively. Values above 10% indicate that the null hypothesis is accepted and there is no causal relationship between the variables. Values below 10% indicate that the null hypothesis is rejected and there is causality between the relevant variables

Based on the BDS test results, nonlinear causality test is applied to the models determined to be nonlinear.

3.3.1. Unit root test results

The stationarity levels of the series are investigated through ADF and PP unit root tests. If the unit root test results are examined, it is observed that the results of both tests are similar. ADF and PP unit root tests state that the stationarity levels of all variables used in the study are I(1). Therefore, for the next stages of the analysis, the first differences of the variables are taken. In Table 2, unit root test results of the series are demonstrated for level.

3.3.2. Quantile causality analysis results

Firstly, the optimal lag length based on information criteria's is determined through VAR analysis. Since most information criteria state that the optimal lag length is 1, the lag length k is considered as 1. In the Table 3 below, the results of lag order selection criteria are examined.

After the determination of optimal lag length, the BDS test is applied. The null hypothesis of the BDS test is based on that the residuals of the estimated model have independent and identical distributions. When the null hypothesis is rejected in the BDS test, it means that the residuals do not have independent and identical distributions. Thus, rejection of null hypothesis refers that the model has a non-linear structure. Table 4 demonstrates the linearity analysis results. Considering BDS test results, it can be stated that all variables have non-linear structure.

On the basis of linearity structures of the series, the quantile causality test results are examined in the next stage of the analysis. In table 5, the quantile causality test results between oil prices, global uncertainty and investor sentiment are evaluated in several quantiles. In the quantile causality test, the null hypothesis (≠>) is that there is no causality between the relevant variables. The results can be summarized as follows:

- The quantile causality test results between oil prices, global uncertainty and investor sentiment revealed that there is no causal relationship between global uncertainty index and oil prices; therefore, global uncertainty does not affect oil prices. On the other hand, investor sentiment has quite significant effects on oil prices. A causal relationship is found between investor sentiment and oil prices both in the median and in several quantiles.
- The quantile causality test results between investor sentiment-oil prices- global uncertainty state that there is no causal relationship between oil prices and investor sentiment. In this context, it is provided that in the energy market oil prices do not affect the interest of investors to the market. In contrast, between global uncertainty and investor sentiment, there is causal relationship in 0.6-0.8 quantiles. This result reveals the role of global uncertainty on investors around the world as market participants.
- The results of quantile causality test between oil prices and global uncertainty indicate that there is a causal relationship in 0.2-0.6 quantiles values, including the median. Considering the analysis results, it is stated that the pricing of oil is quite significant in the uncertainty environment in the world. In addition, investor sentiment has a strong impact on global uncertainty. Investor sentiment causes global uncertainty excluding 0.1 and 0.9 quantiles.

If the econometric analysis results are evaluated in general, there is a strong causal relationship between global uncertainty and investor sentiment. In addition, oil prices also have a significant effect on global uncertainty. And, while oil prices do not affect investor sentiment, investor sentiment significantly affects oil prices. This situation also reveals that the effect of investor sentiment on the markets should be considered from a very broad perspective, not just financial markets.

4. CONCLUSION

Due to the globalization and technological developments in financial markets in recent years, investment decision-making process becomes more significant. And, it leads caused financial markets to have a dynamic structure that changes over time depending on economic conditions, market trends, technological developments and investor behaviours. Thus, determining the financial investment decision-making process is crucial in terms of improving risk management and reliably predicting price movements. Since financial markets have a dynamic structure and are constantly changing, non-linear analyses provide more reliable results.

In a nutshell, this research study provides a nonlinear causal relationship analysis between energy market, uncertainty and investor sentiment with current data. In the analysis, after detecting the existence of nonlinear structures in the series, quantile causality test is conducted. On the basis of test results, it is stated that investor sentiment significantly affects oil prices. In this context, oil prices and therefore the energy market can be shaped by investor interest and open to speculation. And, it can make energy market more fragile. Additionally, oil prices affect global uncertainty. These results suggest that fluctuations in oil prices due to supply shocks etc. cause uncertainty on a global scale. The stability of the energy market is important for improving uncertainty conditions. Moreover, empirical findings provide that investor sentiment and global uncertainty have an impact on each other. The analysis result proves that these two phenomena trigger each other. While investors' expectations regarding the markets are affected by uncertainty conditions, global uncertainty is also affected by speculative investor behaviours. Finally, countries should develop their economic policies by taking into account that financial markets, especially oil markets, are open to speculation and are affected by global uncertainty conditions. For new studies, investor sentiment can be investigated for different markets in different countries by taking into account other uncertainty conditions. The effect of investor sentiment can be observed by grouping the examined countries according to their economic structures and income levels. In addition, this study can be expanded with new analysis methods.

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