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Analysis of the effect of Energy Prices on Stock Indexes During the Epidemic Crisis

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ABSTRACT

Petroleum and natural gas, which are among the most used energy sources in the world, have a significant impact on financial markets and macroeconomic indicators as they are used as raw materials in many fields. For this reason, US, England, Japan, Russia, Turkey, Brazil, and India, as energy importers and developing countries, may be affected positively or negatively by changes in energy prices. The main purpose of this study is to examine the correlation between Brent oil, crude oil (WTI), and natural gas (NG) prices and Moscow Stock Exchange Index (RTSI), Borsa Istanbul Index (XU100), Bovespa Brazilian Stock Exchange Index (BVSP), Indian National Stock Exchange Nifty 50 Index (NSEI), Standard and Poor's 500 Index (S and P 500), London Stock Exchange (FTSE 100), and Tokyo Stock Exchange (N225). In the study, weekly data between February 16, 2020 and December 26, 2021 were examined. Vector autoregressive (VAR) model was used to examine the correlation between the variables included in the analysis, and the direction of the correlation between the variables was determined by the Granger causality test. According to the results of the VAR model, Brent oil and crude oil prices have significant effects on the indices included in the analysis; however, natural gas price does not have a significant effect on indices, Brent oil, and crude oil prices. On the other hand, the results of the Granger causality test confirm the findings of the VAR analysis. Granger causality test results reveal that in Granger's sense, only BVSP and NSEI are the cause of Brent oil price, RTSI, BVSP, NSEI, XU100, S and P 500, FTSE 100, and N225 are the cause of WTI, and WTI is the cause of NSEI.

Keywords: Brent Oil, Crude Oil, Natural Gas, Stock Market İndex, VAR Analysis, Granger Causality
JEL Classifications: B26, C58, G14, G15, O16

1. INTRODUCTION

Stocks reflect enterprises' potential profitability. Therefore, oil shocks' influence on the stock market is a helpful economic indicator. Since asset prices reflect organisations' future net earnings, it's important to lessen the effects of present and future oil shocks on stocks and returns before they happen (Jones et al., 2004 p. 13).

In the simplest sense, energy, which is the basis of life, is vital for the survival and development of humanity (Fouquet, 2011 p. 1). With the mechanisation of production and the production of steam-powered machines, the need for energy has continuously increased, and economic growth and prosperity have become more dependent on energy (Ghosh, 2002 p. 125). It is necessary to consume energy at a certain level in order to achieve rapid economic development (Özdemir, 2012 p. 61). Energy is one of the most important factors that directly or indirectly determines the production level, national and international competitiveness, budget balances, current account deficits, and economic growth levels of countries (Esen, 2013 p. 48, 49). In this respect, for the continuity of economic growth, it is important to provide timely, low-cost, high-quality, reliable energy sources (Bayraktutan et al., 2012 p. 30). Determining the factors affecting stock prices will enable the investor to make the right investment decisions. If the factors affecting the stock prices are determined correctly, the success of the investments to be made will be higher. Factors affecting stock prices are macroeconomic, enterprise-specific, and

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other (Dizdarlar and Derindere, 2008 p. 113). Macroeconomic factors: interest rates, inflation, exchange rates, money supply, economic growth, industrial production index, gold prices, foreign trade balance, foreign portfolio investments, and energy price changes (Güngör and Yerdelen, 2015 p. 149). Microeconomic factors: Capital structure, profit distribution policies, corporate governance, intellectual capital, insider trading, and financial ratios (Demir, 2001 p. 110). Other factors are psychological factors, political factors, seasonal changes, and speculation (Kaya et al., 2015 p. 167).

The effect of energy prices on national economies and financial markets varies depending on whether the country is an energy importer or exporter. Countries that import the majority of energy can be adversely affected by changes in energy prices. For this reason, the long and short-term correlations between energy prices (oil and natural gas) and stock market indices of four developing countries were examined in this study. In this direction, the study is important as it will help the investors who are present and who aim to invest in the Brent oil, Crude oil, and Natural Gas prices, and Moscow Stock Exchange Index, Borsa Istanbul Index, Bovespa Brazilian Stock Exchange Index, Indian National Stock Exchange Nifty 50 Index, Standard and Poor's 500 Index, London Stock Exchange, and Tokyo Stock Exchange in the decision-making process.

The study consists of four parts. In the first part of the study, a literature review related to the studies on this subject was made. In other words, studies on the effects of volatility in energy resource prices on the stock market indices of developed and developing countries have been conducted. In the second part of the study, information is given about the definition of the variables to be analysed and the methods to be used in the analysis. In the third part of the study, the findings obtained as a result of the analysis of dependent and independent variables are included and interpreted. In the conclusion part, which constitutes the fourth chapter, a general evaluation of the study was made.

2. LITERATURE REVIEW

In this section, studies on energy price changes and stock market indices are discussed, and the results of the studies examined in this direction are presented. The number of academic studies is increasing day by day due to the importance of energy and the volatility of its prices.

Price fluctuations in one market can rapidly propagate other markets. In recent decades, there has been much research effort to study the relationship between gold, crude oil, and the stock markets (Gujarati, 2013; Jain and Biswal, 2016; Coronado et al., 2018; Tursoy and Faisal, 2018; Shabbir and Kousar, 2020; Shaikh, 2021), and discover evidence from developed or emerging markets yielding various results. (Samanta and Zadeh, 2012; Partalidou et al., 2016; Raza et al., 2016; Arfaoui and Rejeb, 2017; Wei and Guo, 2017; Karhan and Aydın, 2018; Pandey and Vipul, 2018; Alio et al., 2019; Singhal et al., 2019; Kumar et al., 2019; Majidli and Guliyev, 2020; Kumar et al., 2021; Kumau et al., 2020; Gherghina et al., 2020; Humbatova et al., 2020; Karakuş, 2021). Some of the empirical studies employed vector autoregressive model (VAR) (Ding et al., 2016; Chkili, 2022; Grabias, 2022; Nairobi et al., 2022; Kelesbayev et al., 2022). However, not a single study was able to explain the specific relationship between gold, crude oil, and the stock market (Uthumrat, 2022 p. 350-356.). In recent decades, there has been much research effort to study the relationship between the effect of energy prices on stock ındices in the period of COVID-19, and relationship between oil prices and stock ındustry ındex prices Akbulaev and Rahimli (2020). Suleymanli et al. (2020) Akbulaev et al. (2022).

Between 2001 and 2010, Managi and Okimoto (2013) used MarkovSwitching VAR (MS-VAR) analysis to detect the existence of a relationship between oil, energy company stocks, and interest in the United States. As a result of the analysis, they found a positive relationship between oil prices and stocks. Dhaoui and Khraief (2014) used the EGARCH method to examine whether the stock returns of the USA, Switzerland, France, Canada, England, Japan, Singapore, and Australia countries were affected by oil shocks between January 1991 and September 2013. As a result of the analysis, they found that returns were significantly affected, with decreased returns and increased volatility. They stated that this was due to the risk of an increase in oil prices and the uncertainty in the market.

Benkraiem et al. (2018) examined whether there is a relationship between S&P 500 monthly price data and oil and natural gas prices in the USA between January 1999 and September 2015 using the QARDL-ECM method. They discovered an unstable long-and short-term relationship as a result of the analysis, despite the fact that the amounts were insignificant, and emphasised that energy prices were the driving force for stock market returns.

Alsufyani and Sarmidi (2020) examined the relationship between commodity energy prices and the stock market in Saudi Arabia between the years 2007 and 2017 using the GARCH-X method. As a result of the analysis, they determined that energy prices did not affect the stock market and that there were other macroeconomic factors affecting the stock market.

Chien et al. (2021) analysed the relationship between the COVID-19 pandemic, oil prices, US geopolitical risk index, stock market indices, and the Granger causality test in the USA, Europe, and China. As a result of the analysis, a 1% severity of the pandemic has caused a decrease of around 10% in the productivity index, 0.9% in oil demand, 0.67% in the stock market, 1.12% in GDP growth, and 0.65% in the electricity demand index. They found out why.

Çevik et al. (2020) investigated the relationship between oil prices and stock market returns between 1990 and 2017 using the EGARCH method. As a result of the analysis, they determined that oil prices significantly affect stock returns.

Özcan and Karter (2020) used the Bostrap Rolling Windov causality test to investigate the relationship between oil prices and the BIST100 index between 2001 and 2020. According to the analysis' findings, there is causality from oil prices to the BIST100 index in six periods and in three periods if oil prices from the

BIST 100 are correct, and it would be beneficial for investors to monitor changes in oil prices.

Dursun and Ozcan (2019) constructed a panel data collection using 2005-2017 quarterly OECD data. A multiple structural break cointegration study demonstrated a long-term cointegration between electricity, natural gas, and oil price indices and OECD stock market indices. Energy prices and stock indexes move in the same way. Granfger's causality research shows a link between stock market indices and oil and natural gas prices, but not electricity costs.

Kuzu (2019) analysed the spillover effects of exchange rates, government debt securities, and oil prices on the BIST 100 index, using the data from January 2, 2005, to May 31, 2018, and the EGARCH model. The results of the analysis showed that there is a significant average volatility spillover effect between the government debt securities and the stock market, and this effect is bidirectional.

Corbet et al. (2020) discussed sectoral volatility spillovers in terms of the COVID-19 outbreak, specific to energy companies. As a result, they found significant spillover effects from oil prices on renewable energy and coal prices.

Rakshit and Neog (2021) investigated the effects of volatility in exchange rates, oil prices, and COVID-19 cases on the returns and volatility of stock markets and found that the volatility in exchange rates had a negative effect on the returns of stock markets in Brazil, Chile, India, Mexico, and Russia. They are determined.

Wang et al. (2021) examined the volatility spillovers between stock markets, exchange rates, and oil prices and suggested that volatility spillovers peaked at the beginning of the COVID-19 outbreak and then declined.

Hung and Vo (2021) focused on the spillover effects between the S&P 500 index, oil, and gold prices. They benefited from wavelet coherence and the Diebold-Yilmaz Index. As a result of their study, they determined that return spreads are more intense during the COVID-19 period.

Ajmi et al. (2021), using the BEKK-GARCH model, discussed the volatility spillovers between the US stock market, oil, and gold during the COVID-19 period and determined that the intensity of the spreads between the markets increased during the pandemic period.

Amar et al. (2021) investigated the spreads and co-movements between commodity and stock prices during the COVID-19 period. Using econometric methods such as the Dieboldnd co-movements between commodity and stock prices during the COVID-19 period. Using econometric methods such as the Diebold–Ylmaz Index, the researchers stated that the spreads between the markets included in the study changed according to time, and the highest spread levels were reached during the COVID-19 period.

Kök and Nazlolu (2022) analysed the study's annual data for Brazil, Russia, India, China, South Africa, and Turkey using the stock market index, oil price, and international energy security risk index score covering the period of 1994-2018. As a result of the research, it has revealed the importance of financial markets in terms of energy security risk in the energy-finance relationship for BRICS-T countries.

In their study, Gül and Suyadal (2022) examined the dynamic interdependence relationships between 11 stock markets before and during the COVID-19 pandemic. The research findings show that the relationships between the stock markets have increased during the COVID-19 pandemic. When the literature is examined, the general opinion is that there is an interaction between energy prices and stock market indices, or from stock market indices to energy prices. For this reason, during the pandemic period of February 16, 2020-December 26, 2021, which is thought to be an interaction in the research, Brent oil, crude oil (WTI), and natural gas (NG) prices, the Moscow Stock Exchange Index (RTSI), the Borsa Istanbul Index (XU100), and the Bovespa Brazilian Index The presence of the effect will be investigated in the Boston Stock Exchange Index (BVSP), Indian National Stock Exchange Nifty 50 Index (NSEI), Standard and Poor's 500 Index (S and P 500), London Stock Exchange (FTSE 100), and Tokyo Stock Exchange (N225) indices.

3. DATASET AND ECONOMETRIC METHOD

3.1. Dataset

In this study, the correlation between Brent oil, crude oil (WTI), and natural gas (NG) prices and the indicators of four important capital markets was examined. These four capital market indicators include RTSI-Moscow Stock Exchange Index, XU100-Borsa Istanbul Index, BVSP-Brazilian Stock Exchange Index, NSEI-Indian Stock Exchange Index (in US dollars), S&P 500-Standard and Poor's 500 Index, FTSE 100-London Stock Exchange, and N225-Tokyo Stock Exchange. To investigate the correlation between Brent oil, crude oil (WTI), and natural gas (NG) prices and RTSI-Moscow Stock Exchange Index, XU100-Borsa Istanbul Index, BVSP-Brazilian Stock Exchange Index, NSEI-Indian Stock Exchange Index, S&P 500-Standard and Poor's 500 Index, FTSE 100-London Stock Exchange, and N225-Tokyo Stock Exchange. 97-week data for the period of February 16, 2020-December 26, 2021, when large price fluctuations were observed in energy prices, were used. Vector autoregressive model was used to examine the correlation between the variables, and the direction of the correlation between the variables was determined by the Granger causality test. In this study, all analyzes were carried out with the help of the EViews 12 software package. Table 1 presents the coding and description of the data included in the analysis.

3.2. Methodology

This section describes the methods used to choose the right model in studying the correlation between energy prices and stock market indices. An ordinary time series analysis may be appropriate if all the variables are stationary; however, if they are not stationary, a cointegration analysis, vector error correction (VEC) model, or vector autoregressive (VAR) model may be the appropriate model to test this correlation. Therefore, this section begins with an explanation of stationarity tests. After the stationarity tests, the VAR model and the Granger causality test are explained.

3.2.1. Stationarity tests

Stationarity is one of the most critical properties of time series data. With non-stationary series, it is possible to conclude the analysis with a “spurious regression.” On the other hand, having non-stationary data does not always mean that the correlation between these variables causes spurious regression. If the variables are cointegrated in their level form, the regression results will show their long-run equilibrium correlations.

There are several methods of testing whether the variables satisfy the stationarity condition. One of the methods of testing the stationarity of the said variables is the unit root test. The presence of a unit root in the variables proves that there is no stationarity. In this study, the Augmented Dickey-Fuller test, which is obtained from the Dickey-Fuller test, was used as a unit root test. The following three equations can be used in the traditional Dickey-Fuller test (Syzdykova and Azretbergenova, 2021:50):

$$\Delta yt = \beta 1 * yt - 1 + \varepsilon t$$

$$\Delta yt = \beta 0 + \beta 1 * yt - 1 + \varepsilon t$$

$$\Delta yt = \beta 0 + \beta 1 * yt - 1 + \beta 2 * Trend + \varepsilon t$$

In all three tests, the hypothesis is as follows:

H0: $\beta 1 = 0$ The variable has a unit root, the variable is not stationary.

H1: $\beta 1 < 0$ The variable has no unit root, the variable is stationary.

3.2.2. Vector autoregressive model

The possibility of endogeneity can bias traditional multilinear model estimates. At this point, the vector autoregressive (VAR) model is a suitable model designed to deal with endogeneity problems. In the VAR model, all variables are considered endogenous and their effects on each other are taken into account. In these models, an equation is created for each variable. In these equations, each variable becomes the dependent variable, and the lagged values of the dependent variable and the lagged values of the independent variables are added to the equation. In the end, there will be as many equations as the number of variables. Thus, the effect of each variable on other variables can be tested. The VAR model will use the following systems of equations for the two variables (Syzdykova and Azretbergenova, 2021: 50):

$$Y_t = a_0 + \sum_{i=1}^{m} \beta_i Y_{t-1} + \sum_{i=1}^{m} \beta_i X_{t-i} + \varepsilon_t \tag{1}$$

$$X_t = a_0 + \sum_{i=1}^{m} \beta_i Y_{t-1} + \sum_{i=1}^{m} \beta_i X_{t-i} + \varepsilon_t \tag{2}$$

VAR analysis requires determining the optimal lag length. In the above equations, *m* refers to the optimal lag. Depending on the information criteria, the appropriate lag length is selected. The information criteria used in this study are Likelihood Ratio (LR), Final Prediction Error (FPE), Hannan-Quinn (HQ), Schwarz (SIC), Akaike (AIC). The lower the information criteria of the model, the more appropriate the lag length used in that model. However, information criteria alone are not sufficient to decide the optimal lag length. Serial correlation is a very critical problem in VAR analysis, as the VAR model includes the lagged value of the dependent variable. Therefore, before determining the optimal lag, model results with that lag should be tested for serial correlation. The appropriate lag length can only be chosen after it has been found that the error terms are not serially related.

3.2.3. Vector error correction model, VECM

After proving the existence of a long-term relationship between the series, it is necessary to show the short-term movements of the variables that are related in the long-term. The short-term analysis of the VAR model is done with the vector error correction mechanism. The error correction model allows one to distinguish between the long-term equilibrium between the variables and the short-term dynamics and determine the short-term dynamics. For this purpose, an error correction term reflecting the adjustment to the long-term equilibrium is added between the explanatory variables by taking the first-order differences of the non-stationary variables (Lebe and Akbaş, 2014:67).

If there is a cointegration relationship between the variables, short- and long-term causal relationships can be examined in terms of VECM. Within the scope of this model, even if the series are not stationary, the causality relationship between the variables is questioned without any difference, so information loss about the series is prevented. If the series consisting of X and Y variables are assumed to be dependent variables, respectively, VECM models can be expressed with the help of equations (3) and (4) below (Turan, 2018: 205).

$$\Delta \ln Y_t = a_1 + \sum_{i=1}^{k} \beta_i \Delta X_{t-1} + \sum_{i=1}^{k} \theta_{1i} \Delta Y_{t-1} + \mu VECT_{t-1} + \varepsilon_{1t} \tag{3}$$

$$\Delta \ln X_t = a_2 + \sum_{i=1}^{k} \beta_{2i} \Delta X_{t-1} + \sum_{i=1}^{k} \theta_{2i} \Delta Y_{t-1} + \mu VECT_{t-1} + \varepsilon_{2t} \tag{4}$$

In equations (3) and (4), k represents the optimal delay length, and VECT represents the error correction term. The coefficient in front of the VECT term indicates the vector error correction coefficient and expresses the speed of adaptation of the post-shock imbalances to the equilibrium level over time. If the VECT coefficient is negative, between 0 and 1, and is statistically significant, it will be understood that the established VECM model is correct and the long-term causal relationship between the variables is valid. Diagnostic analysis based on several tests is required to determine whether the established VECM model is robust. The diagnostic tests mentioned above include autocorrelation, varying variance, and normality tests. The existence of serial correlation between the residuals of the model established up to a certain lag length is examined by an autocorrelation test. The autocorrelation test is based on the LM test statistic. If the probability value for all delay values is greater than 5%, it can be concluded that there is no autocorrelation. This shows that the model is a good one. Another method used to measure the robustness of the model is the variable variance test.

The changing variance test is based on the Chi-Square test statistic. If the probability of the Chi-square test statistic calculated for the model is greater than 1%, it is understood that there is no problem of varying variance. Finally, the established VECM model's residues should follow the multivariate normal distribution (Mert and alar, 2019: 273). The normality test is based on the Jarque-Bera test statistic. If the probability of the Jarque-Bera test statistic is greater than 1%, it is understood that the model satisfies the normality condition. As a result, in a well-established VECM model, the VECT coefficient should be negative, between 0 and 1, statistically significant, there should be no autocorrelation and varying variance problems in terms of the residuals of the model, and the residuals of the model should be in accordance with the normal distribution (Tayyar, 2021: 273-274).

Although the cointegration relationship shows long-term relationships between the variables, it does not indicate whether the variables used are internal or external. In terms of establishing the VECM model, it is very important whether the variables are internal or external (Salam & Yldrm, 2014: 203). For this reason, the equation accuracy of the model can be determined by applying the weak externality test to each series. The weak externality test is based on the Chi-square test statistic. By giving a constraint to the related variable, its connection with other series is eliminated in the cointegration relationship. If the chi-square probability value of the variable is less than 1% or 5%, it is understood that the relevant variable is an endogenous variable (Tayyar, 2021: 273-274).

3.2.4. Granger causality test

The significant side in regression analysis is the dependence of one variable on other variables. However, this does not always mean that there is causality between these variables. In other words, causality or the direction of the effect cannot be proved by the existence of a correlation between the variables (Gujarati, 2013: 652).

The Granger causality test consists of estimating the following regression systems (Syzdykova and Azretbergenova, 2021: 51):

$$Y_t = \sum_{i=1}^{m} \beta_i Y_{t-1} + \sum_{i=0}^{m} a_i X_{t-i} + \varepsilon_i \tag{5}$$

$$Y_t = \sum_{i=1}^{m} \gamma_i Y_{t-i} + \sum_{i=0}^{n} \delta_i X_{t-i} + \varepsilon_i \tag{6}$$

Using these models, the Granger Causality test reveals not only the significance of the correlation between variables but also the direction of the correlation between these variables.

4. EMPIRICAL RESULTS

To determine whether there is a multicollinearity problem between the variables used in the study, first of all, the correlation between the variables is examined. Table 2 below shows the correlation matrix between independent variables.

4.1. Unit Root Test

To test the stationarity in the data, study incorporated the Augmented Dicky-Fuller Test. The results statistics are as follows:

As seen in Table 2, according to the above test statistics, all variables are non-stationary at level. As we can see, Brent has a t-statistic of −8.65 with a P-value near zero at the first difference level. This means that the study cannot proceed with regression with the variable BRENT's first difference. NG have a −10.31 value of the t-statistic, which is also highly significant and shows the first differential is better. Like these two, our variable WTI is also stationary at the first difference. As per the above results, all variables based on stock market indices are also significant with respect to the first difference.

4.2. Descriptive Statistics

In this study, the data have been described with the help of descriptive analysis. As we know, the variables incorporated into the study have a unit root problem at level; therefore, the data were initially converted into the first differential for further analysis. Descriptive statistics explain the mean, median, maximum, minimum, standard deviation, skewness, and kurtosis of the data. But the main thing that is explained is the Jarque-Bera statistic. It shows the normality of the data. As per the below results, all variables' data are normally distributed because the probability values of the Jarque-Bera statistic were significant.

Sampling periods and descriptive statistics regarding sampling are given in Table 3. According to the price averages, Bovespa Brazilian Stock Exchange Index (BVSP) has negative averages with a score of −91.32990 and London Stock Exchange with a score of −0.199794 on the basis of the sample period. That is, it has a higher negative return in terms of returns than other countries. Tokyo Stock Exchange (N225) 55.72134 and Indian National Stock Exchange Nifty 50 Index (NSEI) 54,36289, with the highest average, has higher returns for the sample period compared to other countries. Standard and Poor's 500 Index (S&P 500) 14.84536 and Borsa Istanbul Index (XU100) 7.106804 averages

Table 1: Dataset information

Variable	Description
BRENT	Brent oil futures
WTI	Crude oil WTI futures
NG	Natural gas futures
RTSI	RTSI (IRTS) moscow-moscow stock exchange ındex
BIST100	BIST 100 (XU100) ıstanbul-borsa ıstanbul ındex
BVSPO	Bovespa (BVSP)-bovespa brazilian stock exchange ındex
NSEI	Nifty 50 (NSEI)-Indian national stock exchange
SP500	S&P 500 (SPX)-Standard and poor's 500 ındex
FTSE100	FTSE 100 (FTSE)-London stock exchange
N225	Nikkei 225 (N225)-Tokyo stock exchange

Table 2: Augmented Dickey-Fuller test statistic

Variable	*t*-statistic	P-value	Stationary level
BRENT	−8.654948	0.0000	1st difference
NG	−10.31618	0.0000	1st difference
WTI	−8.035219	0.0000	1st difference
RTSI	−9.658492	0.0000	1st difference
BIST100	−8.523583	0.0000	1st difference
BVSPO	−8.816050	0.0000	1st difference
NSEI	−7.163876	0.0000	1st difference
SP500	−11.71144	0.0001	1st difference
FTSE100	−10.83087	0.0000	1st difference
N225	−7.723180	0.0000	1st difference

Table 3: Descriptive statistics based on first difference of variables

Variable	DBRENT	DNG	DWTI	DRTSI	DBIST100	DBVSPO	DNSEI	DSP500	DFTSE100	DN225
Mean	0.198763	0.018814	0.225052	0.732474	7.106804	−91.32990	54.36289	14.84536	−0.199794	55.72134
Median	0.430000	0.032000	0.470000	7.110000	13.60000	−73.00000	133.6500	28.20000	4.560000	74.22000
Maximum	9.180000	0.519000	6.830000	111.6800	134.0000	8144.000	1289.650	301.2000	427.1600	2836.600
Minimum	−11.42000	−1.315000	−9.550000	−266.2700	−193.1900	−15609.00	−1209.750	−406.1000	−1096.440	−3318.700
SD	3.304206	0.247618	3.266174	59.19468	52.85827	4073.209	393.8338	105.2938	205.0327	825.2497
Skewness	−0.522792	−1.760721	−0.823189	−1.425213	−0.982526	−1.104221	−0.385984	−1.084831	−1.945342	−0.488255
Kurtosis	4.310279	10.82018	3.900287	7.728323	5.359342	5.906119	4.503449	6.959664	12.51440	6.152467
Jarque-Bera	11.35740	297.2880	14.23102	123.1979	38.10452	53.84610	11.54419	82.39493	427.0472	44.02029
Probability	0.003418	0.000000	0.000812	0.000000	0.000000	0.000000	0.003113	0.000000	0.000000	0.000000
Sum	19.28000	1.825000	21.83000	71.05000	689.3600	−8859.000	5273.200	1440.000	−19.38000	5404.970
Sum Sq. Dev.	1048.107	5.886197	1024.117	336384.9	268223.7	1.59E+09	14890088	1064332.	4035689.	65379557
Observations	97	97	97	97	97	97	97	97	97	97

Table 4: Correlation matrix

Variable	DBRENT	DNG	DWTI	DRTSI	DBIST100	DBVSPO	DNSEI	DSP500	DFTSE100	DN225
DBRENT	1									
DNG	0.0846	1								
DWTI	0.9441	0.0693	1							
DRTSI	0.6361	−0.0062	0.6232	1						
DBIST100	0.2192	−0.1701	0.2364	0.4135	1					
DBVSPO	0.5062	0.0268	0.4814	0.6253	0.4933	1				
DNSEI	0.4144	0.0649	0.4130	0.6263	0.4595	0.6848	1			
DSP500	0.4935	0.1347	0.4913	0.5912	0.4179	0.7290	0.6660	1		
DFTSE100	0.5490	−0.0562	0.5128	0.7642	0.5018	0.7086	0.6060	0.7519	1	
DN225	0.3487	0.0964	0.3386	0.5932	0.4083	0.6141	0.6300	0.6679	0.7124	1

Table 5: Variance inflation factors (VIF ındex)

Variables and VIF	Coefficient	Uncentered	Centered
Variable	Variance	VIF	VIF
C	22.12289	1.010313	NA
DBRENT	18.74304	9.282673	9.248857
DNG	363.8313	1.014153	1.008271
DWTI	19.13658	9.271177	9.226914

Table 6: Unrestricted cointegration rank test (trace)

Hypothesized No. of CE (s)	Eigenvalue	Trace Statistic	0.05 Critical value	Prob.**
None*	0.558555	307.7303	239.2354	0.0000
At most 1*	0.525815	229.2308	197.3709	0.0005
At most 2	0.311269	157.5997	159.5297	0.0634
At most 3	0.299913	121.8009	125.6154	0.0835
At most 4	0.283212	87.57202	95.75366	0.1600
At most 5	0.208537	55.60644	69.81889	0.3940
At most 6	0.135120	33.15470	47.85613	0.5483
At most 7	0.107538	19.21894	29.79707	0.4773
At most 8	0.082449	8.296846	15.49471	0.4342
At most 9	0.000379	0.036365	3.841466	0.8487

Trace test indicates 2 cointegrating eqn (s) at the 0.05 level. *Denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-Haug-Michelis (1999) P-values

are seen to have medium returns. Moscow Stock Exchange Index (RTSI) 0.732474, crude oil (WTI) 0.225052, Brent oil (BRENT) 0.198763 and Natural Gas (NG) 0.018814 averages seem to have the lowest returns.

Since the high standard deviation, which is another important definitional indicator, indicates an increase in volatility, it is seen that this indicator is ranked from high risk to low risk in Brazil, Japan, England, India, the USA, Russia, and Turkey on the basis of the stock market index. In terms of risk score, it is seen that Russia's score is at the highest level of volatility. In addition, Jarque Bera test statistics obtained from Skewness and Kurtosis statistics show that all series have normal distributions except for the Turkey and Russia data. According to the standard deviation indicators, it is ranked from the ones with both high volatility and high risk to the least. It would be important to state that Brent oil (3.304206), crude oil (3.266174), and natural gas (0.247618), which are the main energy sources known for their sudden price increases or decreases especially during economic, financial, war, and epidemic crises, have the lowest risk with their standard deviations.

Table 7: Unrestricted cointegration rank test (maximum eigenvalue)

Hypothesized No. of CE (s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical value	Prob.**
None*	0.558555	78.49944	64.50472	0.0014
At most 1*	0.525815	71.63115	58.43354	0.0016
At most 2	0.311269	35.79878	52.36261	0.7520
At most 3	0.299913	34.22885	46.23142	0.5099
At most 4	0.283212	31.96558	40.07757	0.3049
At most 5	0.208537	22.45174	33.87687	0.5727
At most 6	0.135120	13.93576	27.58434	0.8270
At most 7	0.107538	10.92210	21.13162	0.6551
At most 8	0.082449	8.260481	14.26460	0.3528
At most 9	0.000379	0.036365	3.841466	0.8487

Max-eigenvalue test indicates 2 cointegrating eqn (s) at the 0.05 level. *Denotes rejection of the hypothesis at the 0.05 level. **MacKinnon-haug-michelis (1999) P-values

4.3. Correlation Analysis

Table 4 presents the correlation analysis result table. In this section, we discuss the correlation analysis of our data. BRENT is strongly correlated with the RTS Index, and both are directly related to

Table 8: Lag order selection criteria

VAR lag order selection criteria Endogenous variables: BRENT NG WTI RTSI BIST100 BVSPO NSEI SP500 FTSE100 N225						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	−5187.958	NA	5.63e+36	112.9991	113.2732	113.1097
1	−4428.898	1336.606	3.41e+30	98.67170	101.6869*	99.88865*
2	−4331.945	149.6444	3.91e+30	98.73794	104.4942	101.0612
3	−4251.102	107.2056	7.19e+30	99.15439	107.6517	102.5840
4	−4107.397	159.3249	4.14e+30	98.20428	109.4427	102.7402
5	−3952.995	137.6189	2.64e+30	97.02164	111.0011	102.6639
6	−3762.423	128.4289*	1.35e+30*	95.05268*	111.7732	101.8012

*Indicates lag order selected by the criterion

Table 9: Vector autoregressive model results

Statistics output and variable	BRENT	NG	WTI	RTSI	BIST100	BVSPO	NSEI	SP500	FTSE100	N225
R-squared	0.974097	0.966539	0.974198	0.950041	0.962341	0.943222	0.985518	0.976600	0.912345	0.959774
Adj.R-squared	0.971085	0.962648	0.971197	0.944232	0.957961	0.936619	0.983834	0.973879	0.902152	0.955096
Sum sq. resids	728.0609	4.095312	764.0154	266391.1	224751.2	1.19E+09	11454324	879950.0	2651285.	51874394
S.E. equation	2.909609	0.218220	2.980587	55.65582	51.12129	3719.447	364.9518	101.1532	175.5816	776.6535
F-statistic	323.4107	248.4133	324.7030	163.5404	219.7621	142.8661	585.2272	358.9180	89.51166	205.1904
Log likelihood	−235.3972	15.85907	−237.7351	−521.6605	−513.4169	−929.2684	−704.0766	−579.6131	−633.1055	−777.3338
Akaike AIC	5.080355	−0.100187	5.128558	10.98269	10.81272	19.38698	14.74385	12.17759	13.28053	16.25431
Schwarz SC	5.372332	0.191791	5.420536	11.27467	11.10470	19.67896	15.03583	12.46957	13.57250	16.54628
Mean dependent	56.83412	2.994773	53.79763	1421.877	1334.686	107003.3	13704.27	3784.499	6554.477	25907.04
SD dependent	17.11099	1.129110	17.56248	235.6765	249.3321	14774.08	2870.317	625.8690	561.3112	3665.099

Determinant resid covariance (dof adj.): 4.36E+30, Determinant resid covariance: 1.31E+30, Log likelihood: −4739.625, Akaike information criterion: 99.99228, Schwarz criterion: 102.9121

Table 10: Vector error correction model results

Error correction:	D (BRENT)	D (NG)	D (WTI)	D (RTSI)	D (BIST100)	D (BVSPO)	D (NSEI)	D (SP500)	D (FTSE100)	D (N225)
CointEq1	−0.496842	−0.046765	−0.365810	0.518457	1.944733	−110.2825	26.32373	−8.674123	−16.02876	−78.99497
	(0.15420)	(0.01119)	(0.15609)	(2.90900)	(2.59037)	(199.883)	(19.1680)	(5.09822)	(9.94251)	(39.7440)
	(−3.22210)	(−4.18104)	(−2.34363)	(0.17823)	(0.75075)	(−0.55174)	(1.37331)	(−1.70140)	(−1.61215)	(−1.98759)
C	0.198763	0.018814	0.225052	0.732474	7.106804	−91.32990	54.36289	14.84536	−0.199794	55.72134
	(0.32021)	(0.02323)	(0.32413)	(6.04085)	(5.37918)	(415.078)	(39.8045)	(10.5870)	(20.6467)	(82.5327)
	(0.62073)	(0.81003)	(0.69432)	(0.12125)	(1.32117)	(−0.22003)	(1.36575)	(1.40223)	(−0.00968)	(0.67514)
R-squared	0.098517	0.155413	0.054657	0.000334	0.005898	0.003194	0.019466	0.029570	0.026629	0.039924
Adj. R-squared	0.089028	0.146523	0.044706	−0.010189	−0.004566	−0.007299	0.009145	0.019355	0.016383	0.029818
Sum sq. resids	944.8505	4.971403	968.1426	336272.5	266641.7	1.59E+09	14600237	1032859.	3928220.	62769323
S.E. equation	3.153695	0.228759	3.192331	59.49547	52.97881	4088.046	392.0290	104.2698	203.3462	812.8528
F-statistic	10.38191	17.48106	5.492586	0.031764	0.563633	0.304412	1.885989	2.894772	2.599012	3.950532
Log likelihood	−248.0384	6.456891	−249.2195	−532.9589	−521.7061	−943.2614	−715.8461	−587.3839	−652.1729	−786.5799
Akaike AIC	5.155430	−0.091895	5.179783	11.03008	10.79806	19.48992	14.80095	12.15224	13.48810	16.25938
Schwarz SC	5.208517	−0.038808	5.232869	11.08317	10.85115	19.54301	14.85404	12.20533	13.54119	16.31247
Mean dependent	0.198763	0.018814	0.225052	0.732474	7.106804	−91.32990	54.36289	14.84536	−0.199794	55.72134
SD dependent	3.304206	0.247618	3.266174	59.19468	52.85827	4073.209	393.8338	105.2938	205.0327	825.2497

Determinant resid covariance (dof adj.): 1.30E+31, Determinant resid covariance: 1.06E+31, Log likelihood: −4840.948, Akaike information criterion: 100.4319, Schwarz criterion: 101.2282

each other. BRENT is also moderately directly proportional to BVSPO, NSEI, SP500, FTSE500, and N225, but only weakly correlated with BIST100.

NG has a very weak association with some indices. NG has no significant association with RTSI, BVSPO, NSEI, FTSE100, or N225, but the variable has a weakly significant association with BIST100 and SP500. The NG index has a direct relationship with the SP500 index and an inverse relationship with the BIST100 index. WTI has a strong and positive relationship with RTSI. WTI is positively related to the BIST100, BVSPO, NSEI, SP500, FTSE100, and N225 indices. WTI is weakly related to the BIST100 index, and its relationship with the other 5 indices is moderate. But here the question is: does there exist any statistically significant association between these oil prices and market indices? To test this phenomenon, the study will analyse the data using the VAR and VEC models.

4.4. Testing for Multicollinearity

Before starting any regression analysis, the study tested the model for multicollinearity. To study the multicollinearity, we used the Variance Inflation Factors (VIF) index. There are different schools of thought about the VIF value for multicollinearity, but we go with the common thought. If the VIF value is <10, it means there is no issue of multicollinearity, but if the VIF value is higher than10, it means multicollinearity exists.

As seen in Table 5, the above results are based on the ordinary least squares method. In the above analysis, first the study regresses the model by taking any one index as a dependent variable and BRENT, NG, and WTI as independent variables. The ordinary least squares method was used to detect the VIF index values for regressors. The VIF values indicate that all our variables are free from the issue of multicollinearity.

4.5. Testing for Cointegration

Before going for VAR or VECM, the study tested the data for cointegration equations. The below results are based on Johnson's cointegration test. The cointegration test will reveal whether or not there are any cointegrated equations. If any cointegrated equation exists, it means that the data follow a long-term trend, and we can regress the vector error correction model. As we already tested the data for unit root and unit root exists in the data, it is better to use VAR models with lag selections to eliminate the issue of unit root. As per the below analysis, at most two cointegrating equations can be studied with the help of Johnson's cointegration test. Therefore, we will use both VAR and VECM methods to test the relationship between oil market prices and stock market indices (As seen in Tables 6 and 7).

4.6. Vector Autoregressive Model (VARM)

This work is based on studying the relationship between crude oil, natural gas, and petroleum products using seven different stock market indices. The study uses VAR and VECM methods to test the relationship between oil prices and indices. In this section, we will discuss the lag selection criteria and vector autoregressive analysis.

As seen in Table 8, as per the above analysis, there are different criteria to select the lanes. These lag selection criteria are LR, FPE, AIC, SC, and HQ. LR, FPE, and AIC criteria explain that the lag selection should be six or higher, but in this study, our data is based on limited observations; therefore, we consider the SC and HQ criteria for lag selection. We can accept one lag based on the above analysis. In VAR, we will do analysis with lag 1, and for VECM, we will use lag min 1, e.g., zero lags (Table 9).

As seen in Table 9, as per the above analysis, the Brent oils are positively related, with the RTS index having a P-value near zero. It means we can conclude the results as the brent is highly significantly related with RTS index at 0.01 level of significance. Moreover, the relationship between these variables is positive. Natural gas and crude oil are also positively related to the RTS index, with both being significant at the 0.01 level. The association between Brent oil, crude oil, and natural gas with the BIST100 index is also highly significant and directly proportional to this index. The P-value of these three regressors is significant at the 0.01 level. Brent oil, crude oil, and natural gas variables all have a positive relationship with the BVSPO index. As per the above results, these variables are also highly significant for the NSE index, SP500, FTSE 100, and N225, as the P-values of all regressors were almost zero. As a result, we can conclude that all of the regressors are statistically significant at the 0.01 level and have a positive association.

4.7. Vector Error Correction Model (VECM)

After performing the analysis with the VAR method, the study incorporated VECM as a robustness analysis because there is cointegration, which indicates that a long-term trend is applicable. To test the model under long-term trends, the study uses VECM. Below are results based on a vector error correction model (Table 10).

As per the above analysis, Brent oil is significantly associated with market indices at the 0.05 level of significance. The equation based on Brent oil can explain 9.85% of the total population. The overall significance of the model is good, with an F-statistics value of 10.38. Natural gas is also significant at the 0.05 level, and the model based on natural gas can explain 15.54% of the population. The second model based on natural gas has overall significance with an F-statistic value of 17.48. Moreover, the model based on crude oil is significant only at a 0.1 level. As per the two analyses, the VAR and VECM explain the significant association between Brent oil, crude oil, and natural gas with stock market indices.

4.8. Granger Causality Test

After performing the analysis with VAR and VECM, the study also tested the causal relationship between the indicators. The results presented below are based on the Granger Causality Test, which was run in EViews. As per the below results, the BIST100 index has a positively significant causal relationship with Brent oil at a 0.05 level of significance. Moreover, the NSE index positively causes the Brent oil price, and the SP500 index also has a causal association with Brent oil prices. Both causal relationships are significant.

According to the Granger causality test results shown in Table 11, while the natural gas price is not the cause of Brent Oil (P-values higher than 1%, 5%, and 10%, "0.0151"), it is seen that Brent Petroleum Natural Gas is the cause ($P < 10\%$, "0.0954"). Similarly, while natural gas prices are not the cause of crude oil prices ($P > 1\%$, 5%, and 10%, "0.2121"), crude oil prices are the cause of less ($P < 10\%$, "0.0757"). While the price of crude oil is the cause of Brent oil ($P < 10\%$, "0.0630"), it is seen that Brent oil is not the cause of crude oil (P-value is higher than 1%, 5%, and 10%, "0.5811").

When Table 12 is examined, it is seen that while the RTSI index belonging to the country with oil resources is the cause of Brent Petroleum ($P < 10\%$, "0.0762"), Brent Petroleum is not the cause of the RTSI index (P-value higher than 1%, 5%, and 10% "0.22029"). While BIST100 index is the reason for Brent Oil ($P < 5\%$, "0.0495"), Brent Oil is not the reason for BIST100 index (P-value is higher than 1%, 5%, and 10%, "0.6705"). It is seen that the BVSPO index is not the cause of Brent Oil (P-value

Table 11: Granger causality test of the relationship between energy prices

Null hypothesis	F-statistic	Prob.
NG→BRENT	2.20787	0.1407
BRENT→NG	2.83783	0.0954
NG→WTI	1.57869	0.2121
WTI→NG	3.22541	0.0757
WTI→BRENT	3.54082	0.0630
BRENT→WTI	0.30653	0.5811

higher than 5%, “0.2193”), and Brent Oil is not the cause of the BVSPO index (P-value higher than 1%, 5%, and 10%, “0.6859”). While the NSEI index is the strongest cause of Brent Oil (P < 1%, “0.0002”), Brent Oil is not the cause of the NSEI index (P-value is higher than 1%, 5%, and 10%, “0.8028”). While the SP500 index belonging to the country that owns the oil resources is the strong cause of the Brent Petroleum (P < 1%, “0.0006”), it is seen that the Brent Petroleum is not the cause of the SP500 index (P-value higher than 1%, 5%, and 10%, “0.7242”). Likewise, it is seen that the FTSE100 and N225 indices, Brent Oil, and Brent Oil are not the cause of the FTSE100 and N225 indices (P-values higher than 1%, 5%, and 10%). “FTSE100: 0.9730, Brent: 8.E-05, N225: 6.E-05, Brent: 0.4661,” for example.

As seen in Table 13, the P-value of the test statistics for the RTSI belonging to the country with natural gas resources is 0.0496, which is <5% significance level. The RTSI index is the cause of the natural gas price. The P-value of the test statistics for natural gas is 0.0089, which is <1% significance level. Therefore, the null hypothesis that natural gas and RTSI are the causes is accepted. While it is not the reason for the natural gas price of the BIST100 index of the natural gas-importing country (P-value higher than 1%, 5%, and 10%, “0.5798”), it is seen that the natural gas price is the reason for the BIST100 index (P < 1%, “0.0090”). While the BVSPO index is the cause of the natural gas price (P < 10%, “0.0995”), the natural gas price is not the cause of the BVSPO index (P-value is higher than 1%, 5%, and 10%, “0.9890”). While the NSEI index is the reason for the natural gas price (P < 10%, “0.0692”), the natural gas price is not the reason for the NSEI index (P-value is higher than 1%, 5%, and 10%, “0.1949”). While the SP500 index is the reason for the natural gas price (P < 10%, “0.0825”), the natural gas price is not the reason for the SP500 index (P-value is higher than 1%, 5%, and 10%, “0.6007”). While it is not the reason for the natural gas price of the FTSE 100 index (P-value higher than 1%, 5%, and 10%, “0.3432”), it is seen that the natural gas price is not the reason for the SP 500 index (P < 1%, “0.0011”). It is seen that the N225 index is not the cause of the natural gas price, and the natural gas price is not the cause of the N225 index (P-values higher than 1%, 5%, and 10% “0.2868” and “0.4417”).

Examining Table 14, the RTSI index is the cause of the WTI price (P < 10%, 0.0979). However, it seems that the WTI price is not the cause of the RTSI index (P-value higher than 1%, 5%, and 10%, “0.1750”). It is the reason for the WTI price of the BIST100 index (P < 10%, “0.0710”). It seems that the WTI price is not the cause of the BIST100 index (P-value higher than 1%, 5%, and 10%, “0.6714”). It is seen that the WTI price of the BVSPO index (P-value higher than %, 5%, and 10%, “0.2092”) and WTI are not the cause of the BVSPO index (P-value higher than 1%, 5%, and 10%, “0.7885”). While the NSEI index is the cause of the WTI price (P < 1%, “0.0011”), it is seen that the WTI price is not the cause of the NSEI index (P-value higher than 1%, 5%, and 10%, “0.9949). The strong reason for the WTI price of the SP500 index belongs to the country that owns this oil resource (P < 1%, or “0.0016”). However, it seems that the WTI price is not the cause of the SP500 index (P-value higher than 1%, 5%, and 10%, “0.8309”). Why does the WTI price of the FTSE 100 index change? (The P-value is higher than 1%, 5%, and 10% (“0.7918”). The WTI price appears to be the strong cause of the FTSE 100 index (P < 1%, “0.0001”), while the N225 index is the strong cause of the WTI price (P < 1%, “0.0020”). It seems that the WTI price is not the cause of the N225 index (P-value higher than 1%, 5%, and 10%, “0.5798”).

As a result, it can be said that the Granger causality test results confirmed the findings of the VAR analysis during the COVID-19 pandemic.

Table 12: Granger causality test of the relationship between brent oil prices and stock indices

Null hypothesis	F-statistic	Prob.
RTSI→BRENT	3.21441	0.0762
BRENT→RTSI	1.64452	0.2029
BIST100→BRENT	3.96073	0.0495
BRENT→BIST100	0.18219	0.6705
BVSPO→BRENT	1.52897	0.2193
BRENT→BVSPO	0.16460	0.6859
NSEI→BRENT	15.5201	0.0002
BRENT→NSEI	0.06270	0.8028
SP500→BRENT	12.4966	0.0006
BRENT→SP500	0.12524	0.7242
FTSE100→BRENT	0.00115	0.9730
BRENT→FTSE100	17.1354	8.E-05
N225→BRENT	17.7753	6.E-05
BRENT→N225	0.53568	0.4661

Table 13: Granger causality test of the relationship between natural gas and stock market indices

Null hypothesis	F-statistic	Prob.
RTSI→NG	3.95474	0.0496
NG→RTSI	7.13336	0.0089
BIST100→NG	0.30864	0.5798
NG→BIST100	7.11022	0.0090
BVSPO→NG	2.76849	0.0995
NG→BVSPO	0.00019	0.9890
NSEI→NG	3.37802	0.0692
NG→NSEI	1.70467	0.1949
SP500→NG	3.08032	0.0825
NG→SP500	0.27576	0.6007
FTSE100→NG	0.90765	0.3432
NG→FTSE100	11.2688	0.0011
N225→NG	1.14776	0.2868
NG→N225	0.59700	0.4417

Table 14: Granger causality test of the relationship between crude oil prices and stock indices

Null hypothesis	F-statistic	Prob.
RTSI→WTI	2.79530	0.0979
WTI→RTSI	1.86729	0.1750
BIST100→WTI	3.33554	0.0710
WTI→BIST100	0.18107	0.6714
BVSPO→WTI	1.59909	0.2092
WTI→BVSPO	0.07240	0.7885
NSEI→WTI	11.2549	0.0011
WTI→NSEI	4.1E-05	0.9949
SP500→WTI	10.5796	0.0016
WTI→SP500	0.04587	0.8309
FTSE100→WTI	0.07007	0.7918
WTI→FTSE100	16.5976	0.0001
N225→WTI	15.5635	0.0002
WTI→N225	0.30872	0.5798

5. CONCLUSION

The relationship between energy and capital market indicators is very important for investors as it can affect their diversification decisions. In this study, the correlation between Brent oil, crude oil, and natural gas prices and Moscow Stock Exchange Index, Borsa Istanbul Index, Bovespa Index, Indian Stock Exchange Index, Standard and Poor's 500 Index, London Stock Exchange, and Tokyo Stock Exchange has been studied. In the study, weekly data between 16.02.2020 and 26.12.2021 were examined. Vector autoregressive model was used and the direction of the correlation between variables was determined by the Granger causality test.

Brent oil prices also have a positive causal relationship with the FTSE 100 index and the N225 index. The causal impact is significant at a level of 0.05. Natural gas has a positive effect on the RTS Index and is significant at both the 0.05 and 0.01 levels. Natural gas also has a positive effect on the BIST100 index and is significant at the 0.05 level. The causal association between natural gas and the FTSE 100 index is also positively significant. These results are also similar to our previous VAR and VECM analyses. The NSE index, SP500 index, and N225 index positively cause the price of crude oil, as these variables are significant at the 0.01 level of significance. Finally, crude oil has a positive influence on the FTSE 100 index, which is statistically significant at the 0.01 level. In line with all the above analyses, e.g., correlation, VAR, VECM, and Granger Causality Analysis, there was a significant association studied between Brent Oil, Crude Oil, and Natural Gas Prices with Stock Market Indices.

As a result of the analysis, in summary (i) causality in the price of Brent oil and crude oil natural gas, crude oil Brent oil price at 10% accuracy level; (ii) causality to brent oil price of Russia, Turkey, India and USA stock market indexes; the causality of the Brent oil price only to the Turkish Stock Exchange; (iii) causality to natural gas from the Russian, Brazilian, Indian, and US stock exchanges; Causality from natural gas to stock market indices in Russia, Turkey, and England; (iv) Causal to Crude Oil from stock market indices of Russia, Turkey, India, USA and Japan; It can be said that there is only one causal link between crude oil and the British Stock Exchange Index. There is a causal relationship between stock markets and energy prices. As a result of this study, it shows that oil and natural gas, which are the main energy sources, and capital market investors should follow both the oil and natural gas price changes and the movements in the stock market indices during the pandemic crisis periods as well as during the economic and financial crisis periods. Although the results provided valuable information about the relationships between stock market indices and oil and gas prices, it would be useful to analyze normal periods and compare the results with the findings in this study.

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