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Research Article | Araştırma Makalesi

Examining the dynamic conditional correlation between oil prices and stock prices: Implications for global financial markets and the impact of COVID-19

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Abstract

The dynamic structure of the global economy is one of many factors that affect the fluctuations in the global financial markets. COVID-19, like all other epidemics, has been an important period in human history. Exporting and importing oil are also important distinctions in economies. This study aims to investigate the dynamic relationship between stock market closing prices and Brent oil prices of six major oil-importing and oil-exporting economies during the COVID-19 period. These stock markets have a significant impact on the world economy and serve as reference points for evaluating industry performance. The Dynamic Conditional Correlation (DCC) method are used to model the complex interactions of the energy market and markets. It aims to reveal the relationship between fluctuations in energy prices and other macroeconomic indicators. According to the findings, it is concluded that fluctuations in oil prices have a non-negligible impact on stock markets due to the persistence of ARCH effects and volatility in each financial market. Assuming that volatility continues, it is seen that volatility continues to have an impact on the markets examined.

Keywords: Oil Prices, Stock Prices, Dynamic Correlation, Volatility Persistence, Financial Markets **JEL Codes:** C00, C01

Petrol fiyatları ile hisse senedi fiyatları arasındaki dinamik koşullu korelasyonun incelenmesi: Küresel finans piyasalarına etkileri ve COVID-19'un etkisi

Öz

Küresel ekonominin dinamik yapısı, küresel finansal piyasalardaki dalgalanmaları etkileyen pek çok faktörden biridir. COVID-19 da diğer tüm salgın hastalıklar gibi insanlık tarihinde önemli bir dönem olmuştur. Petrol ihraç etmek ve petrol ithal etmek de ekonomilerde önemli bir ayrımdır. Bu çalışmada, altı önemli petrol ihraç eden ve ithal eden ekonominin borsa kapanış fiyatları ile Brent petrol fiyatları arasındaki dinamik ilişkinin COVID-19 döneminde araştırılması amaçlanmıştır. Bu hisse senedi piyasalarının dünya ekonomisi üzerinde önemli bir etkisi vardır ve endüstri performansının değerlendirilmesinde referans noktası görevi görmektedir. Enerji piyasası ve piyasaların karmaşık etkileşimlerini modellemek amacıyla Dinamik Koşullu Korelasyon (DCC) yöntemi kullanılmıştır. Enerji fiyatlarındaki dalgalanmaların diğer makroekonomik göstergelerle ilişkisini ortaya koymak amaçlanmıştır. Bulgulara göre, her bir finansal piyasadaki ARCH etkilerinin ve volatilitenin kalıcı olması nedeniyle petrol fiyatlarındaki dalgalanmaların hisse senedi piyasaları üzerinde göz ardı edilemeyecek bir etkiye sahip olduğu sonucuna varılmaktadır. Volatilitenin devam ettiği varsayımında, volatilitenin incelenen piyasalar üzerinde etkisinin devam ettiği görülmektedir.

Anahtar Kelimeler: Petrol Fiyatları, Hisse Senedi Fiyatları, Dinamik Korelasyon, Volatilitenin Kalıcılığı, Finansal Piyasalar **JEL Kodları:** C00, C01

Introduction

The ups and downs of the financial markets around the world are a result of a number of factors, including the ongoing flux of the global economy. The price of oil is one of the most crucial of these variables because it has a big impact on the financial, commodity, labor, and industrial production markets, which in turn affects the economic development of both developing and emerging nations. Consequently, both investors and policymakers place great importance on understanding the connection between the price of oil and the stock markets of major economies.

Stock markets can be significantly impacted by the volatility of oil prices. High volatility can lead to significant changes in the energy and oil industries, which can then have an impact on the performance of related sectors. In order to manage market risk and make wise investment decisions, it is crucial for investors and policymakers to understand the relationship between oil prices

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and stock prices.

In this study, we examine the dynamic conditional correlation between the prices of Brent crude oil and the stock prices of six major economies, including S&P TSX60 in Canada, MXICP 35 in Mexico, BOVESPA in Brazil, DAX in Germany, DOW JONES in the United States, and AEX in the Netherlands. Although there are of course many countries that export and import oil, these 6 stock market data has been studied due to the lack of data (Filis et al., 2011).

We attempt to shed light on the complex interactions between the energy market and the economies of these six oil-importing and oil-exporting countries by analyzing the dynamic correlation between oil prices and markets before and after the COVID-19 period. At the same time, the COVID-19 period, which is said to have caused the biggest recession since the Second World War, is examined through oil prices and markets (The World Bank, 2023). For this reason, its contribution to the literature is remarkable. Dynamic Conditional Correlation (DCC) approaches are used to understand the short- and long-term connections between these markets.

The fluctuation in oil prices and how it affects the markets for commodities, labor, and industrial goods have a big impact on the world economy. Numerous studies have examined the asymmetric link between the price of gold and that of oil, the impact of these prices on economic growth, and the significance of both prices' price volatility on business cycle structures. For instance, Bildirici & Sonustun (2018) investigate how fluctuations in the price of oil and gold affected particular oil-exporting nations' economic growth. They recognize the asymmetry in the relationship between these two commodities as well as how it affects the patterns of the business cycle.

Oil prices have a significant impact on the global economy, with high volatility causing major changes in the energy and oil industries. Value at Risk (VaR) is an important risk management tool for protecting against market risk, and Extreme Value Theory (EVT) has been shown to be effective in modeling VaR for long and short trading positions in the oil market, with conditional EVT and Filtered Historical Simulation offering the best results (Marimoutou et al., 2009).

Numerous studies have also looked into how stock returns in various market environments are impacted by crude oil shocks and the unpredictability of economic policy. Quantile regression is employed by You et al. (2017) to examine the asymmetric effects of crude oil shocks and China's unclear economic policy on stock returns, demonstrating that the effects change depending on the state of the market.

Elgammal et al. (2021) examine the dynamic interrelationships between the global equities, gold, and energy markets before and during the COVID-19 epidemic. The study discovers bidirectional return spillovers between equities and gold markets using a bivariate GARCH(p, q) paradigm, as well as unidirectional mean spillovers from energy markets to equity and gold markets and significant reciprocal shock spillovers between equity and energy/gold markets. The strong cross-volatility spillover effect of the energy markets on other markets is also underlined by the study. Again, in this study, focusing on the significant impact of COVID-19 on prices has been an important guide in observing its impact on the economies of oil-importing and oil-exporting countries. Choosing one of the important crisis periods based on this study gives us an important idea about the evaluation of the COVID-19 period.

Studies that look at the relationship between stock market values and oil prices for various nations highlighted the detrimental effects of oil prices on stock markets, with the exception of periods of severe economic unrest. The correlation between the two markets is examined using a DCC-GARCH-GJR approach by Filis et al. (2011), who come to the conclusion that the oil market is not a "safe haven" for guarding against stock market losses.

Choudhry et al. (2015) look at the nonlinear dynamic relationships between gold returns, stock market returns, and stock market volatility during the global financial crisis, demonstrating that gold may not function well as a safe haven during such times but can be used as a hedge against stock market returns and volatility in stable financial conditions. In their analysis of the dynamic correlations and market linkages between climate bonds and US equity, crude oil, and gold markets during stressful periods like the COVID-19 outbreak, Dutta et al. (2021) demonstrate that climate bonds offer significant risk reduction in a portfolio that includes US equity or gold as part of a hedging strategy. Dutta et al. (2021) study draws our attention to COVID-19 for this study.

Adekoya et al. (2021) analyze gold's ability to protect investors during the COVID-19 pandemic from hazards related to stock markets and crude oil. With evidence of time-variation and stronger hedging potentials at higher oil and stock prices, the results point to gold's ability to effectively hedge market risks connected with the global oil and stock markets during this time. This study enlightens us to consider the relationship between oil and markets in a before-and-after manner for the COVID-19 period.

A hybrid wavelet-based Dynamic Conditional Correlation (DCC) methodology is used by (Bhatia et al. (2020) to explore the dynamic relationship between precious metals and stock markets of important developed and developing countries. They discover that palladium is the best metal for building a two-asset optimal portfolio of precious metal and stock index, while silver offers better hedging capabilities than other precious metals in the short and long terms. While working on stock markets, using the Dynamic Conditional Correlation (DCC) method on the markets also helps us decide on the method.

By examining daily stock market indices in six major oil-importing and oil-exporting countries (Netherlands, Germany, United States, Mexico, Canada, and Brazil) together with Brent crude oil prices, we aim to see how the unprecedented global crisis has reshaped market dynamics. This study covers the pre- and post-COVID-19 periods and closely examines how this global health crisis may have changed market dynamics.

Understanding market dynamics in the face of economic turmoil is vital to formulating effective policies, making informed investment decisions, and promoting economic stability. This study makes a valuable contribution to the existing literature in several aspects. Firstly, by comparing the oil prices and stock market relationship before and after the COVID-19 crisis, we provide new insights into how major economic shocks reshape market correlations. Secondly, focusing on both oil-importing and oil-exporting countries provides a detailed understanding of the potentially different effects of oil price fluctuations on these economies. Finally, the methodological rigor of using the DCC model provides a robust analysis of the dynamic and time-changing nature of this vital market relationship.

The Dynamic Conditional Correlation (DCC) method is used, which allows us to capture short-term and long-term correlations between these markets. This provides a more detailed understanding of the relationship between them than traditional correlation methods and thus contributes to the advancement of knowledge in this field.

In this research, we use data from Brent crude oil prices and stock prices of six major economies (Canada, Mexico, Brazil, Germany, the United States, and the Netherlands). These countries are chosen due to their important role in the global oil market and the availability of reliable data. This strategic choice adds a unique dimension to our study by providing a broad yet insightful perspective on the interconnectedness of these economies and the global oil market.

While data on stock market values and Brent oil prices of the relevant countries are used, the dates of restrictions imposed by the countries regarding the COVID-19 period differ from each other. Here, December 1, 2019, is considered the distinguishing date as the period before and after the first case (Huang et al., 2020).

We anticipate that our findings will be of great interest to investors, policymakers, and researchers in understanding the dynamics of markets during periods of economic turmoil and thus improving policy formulation and investment strategies to mitigate the effects of such crises. The importance of our research extends beyond academic circles, as we believe our findings will be of significant value to a variety of stakeholders, including investors, policymakers, and researchers.

The rest of the paper is organized as follows: Section 2 presents the oil price chronology for the period under consideration, Section 3 reviews the literature, Section 4 describes the model and data used, Section 5 presents the empirical findings of the research and, finally, Section 6 concludes the study.

1. Methods

Dynamic Conditional Correlation (DCC) is a statistical technique used to model the correlation between two or more time series data that may vary over time. The traditional approach to modeling correlations between time series is to use the Pearson correlation coefficient, which assumes that the correlation is constant over time. However, in practice, the correlation between time series may change over time due to various factors, such as changes in market conditions, economic factors, or external events.

To address this issue, DCC is proposed as a way to model time-varying correlations. DCC assumes that the correlation between time series is a function of both the current value of each time series and its past volatility. In other words, the correlation between two time series is allowed to vary over time based on how much they have moved in the past.

DCC estimates the time-varying correlation matrix using a two-step process. The first step involves estimating the univariate volatility of each time series using a GARCH model. The second step involves estimating the dynamic conditional correlation matrix using a multivariate GARCH model that incorporates the estimated univariate volatilities. Overall, DCC provides a flexible and robust framework for modeling time-varying correlations between time series, making it particularly useful in financial modeling and risk management.

There are two classifications, VAR-based and GARCH-based methods, to examine financial contagion and volatility spillover. The DCC GARCH method is one of the GARCH-type methods. One model that has been shown to be successful in capturing volatility clustering and predicting future volatility is the univariate GARCH model, an extended version of the ARCH model introduced by Bollerslev in 1986. This model assumes that the volatilities among the variables are constant throughout the period and cannot capture the correlations between multiple time series (Najeeb et al., 2015).

It is essential to take into account the dependence on the movements of asset returns. One method of estimating the covariance matrix between entities is to extend the univariate GARCH to a multivariate GARCH model. It is known that the multivariate GARCH models proposed by Engle & Kroner (1995) to capture the volatility transfer between financial markets are methods that can effectively predict the conditional correlation between financial assets (Singhal & Ghosh, 2016).

The fixed conditional correlation (CCC)-GARCH Bollerslev (1990) model has eliminated the shortcomings of the univariate GARCH model, but it takes the dynamic correlation as constant. On the other hand, Engle (2002) developed a dynamic model that accepts conditional correlation as a time-varying structure. The DCC-GARCH method has several advantages over other multivariate GARCH models, and most importantly, the time-varying correlation coefficients obtained from the model can be used in financial predictions because it takes into account the varying variance by estimating the dynamic correlation coefficients of standardized residuals (Ahmad et al., 2013).

This article introduces a new class of multivariate GARCH estimators that can best be viewed as a generalization of the Bollerslev (1990) constant conditional correlation (CCC) estimator.

Engle (2002) introduced dynamic conditional correlation (DCC), assuming that the correlation coefficient among variables is changing over time, and the model can eventually derive the dynamic correlation coefficient to characterize the dynamic linkage and dependence among multiple variables.

Liow et al. (2009) use the DCC model to estimate the time-varying conditional correlations in international real estate securities and stock markets. Guesmi & Fattoum (2014) utilize the DCC method to provide evidence of the co-movements and dynamic volatility spillovers between stock markets and oil prices among oil-importing and oil-exporting countries.

The general equation of the DCC model developed by Engle (2002) is as given in Equation 1. Here, H_t is conditional covariance matrix which conforms to the Normal Distribution $N(0, E[r_t r_t' | I_{t-1}])$, D_t is diagonal matrix *kxk* with conditional variance of $\sqrt{h_{it}}$ and R_t is a time-varying correlation matrix.

$$H_t = D_t R_t D_t \tag{1}$$

Here, the conditional variance of h_{it} is estimated using the univariate GARCH(X,Y) model as in Equation 2. Where w_i, a_{ix} and β_{iy} are non-negative and with $\sum_{x=1}^{x_i} a_{ix} + \sum_{y=1}^{Y_i} \beta_{iy} < 1$, a_{ix} is the short-term persistence of shocks that returns Y to long-term persistence (GARCH effects). *k* represents the number of assets. 187

$$h_{it} = w_i + \sum_{x=1}^{x_i} a_{ix} r_{it-x}^2 + \sum_{y=1}^{Y_i} \beta_{iy}\, h_{it-y} \quad , i = 1,2,3, \ldots .k \tag{2}$$

The diagonal matrix D_t is given in Equation 3. ε_t shows errors and $\sqrt{h_{it}}$ shows conditional standard deviations.

$$D_t = \begin{bmatrix} \sqrt{h_{11,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots \\ 0 & \cdots & \sqrt{h_{kk,t}} \end{bmatrix} \tag{3}$$

Using the standard errors of $\sigma_{it} = {}^{\varepsilon_{it}}\!/_{\sqrt{h_{it}}}$ the time-varying conditional correlation matrix R_t is calculated as in Equation 4.

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{4}$$

Here Q_t^* is defined as given in Equation 5.

$$Q_t^* = \begin{bmatrix} \sqrt{\sigma_{11,t}} & \cdots & 0 \\ \vdots & \vdots & \vdots \\ 0 & \cdots & \sqrt{\sigma_{kk,t}} \end{bmatrix} \tag{5}$$

A symmetric positive descriptive conditional covariance matrix Q_t is calculated as shown in Equation 6, where $Q_t = (q_{ij,t})$ and $\bar{Q}$ the unconditional correlation of the standardicze errors of the single GARCH model.

$$Q_t = (1 - a - b)\bar{Q} + \alpha\varepsilon_{t-1} - 1\varepsilon_{t-1}' + bQ_{t-1} \tag{6}$$

Conditional correlation $\rho_{ij,t} = {}^{q_{ij,t}}\!/_{\sqrt{q_{i,j,t}q_{i,j,t}}}$ by putting $Q_t = \left(q_{ij,t}\right)$ in a typical correlation can be expressed as in Equation 7.

$$\rho_{ij,t} = \frac{(1-a-b)\bar{Q}+\alpha\varepsilon_{t-1}-1\varepsilon_{t-1}'+bQ_{t-1}}{\sqrt{(1-a-b)\bar{Q}+\alpha\varepsilon_{t-1}-1\varepsilon_{t-1}'+bQ_{t-1}}\sqrt{(1-a-b)\bar{Q}+\alpha\varepsilon_{t-1}-1\varepsilon_{t-1}'+bQ_{t-1}}} \tag{7}$$

In parameter estimation of the DCC model, we first estimate the univariate GARCH model for each market return to obtain the standard residuals; then, the dynamic conditional correlation coefficients of the model are estimated with standard residuals.

2. Application

For this study, we utilize daily data on oil prices and stock market indexes. Three oil-importing nations— the AEX in the Netherlands, the DAX in Germany, and the DOW JONES in the United States—as well as three oil-exporting nations— the MXICP 35 in Mexico, the S&P TSX60 in Canada, and the BOVESPA in Brazil—make up the sample (Yahoo Finance, 2023). Three requirements have to be met in order to establish the sample: The top 20 oil importers and exporters are evaluated, all nations should have well-developed stock markets and a careful balance between existing stock markets and emerging stock markets is taken into account (Filis et al., 2011).

In 2021, the United States continued to be a net importer of crude oil, buying 6.11 million b/d and exporting 2.96 million b/d respectively. Germany ranked sixth globally in terms of crude imports in 2017, bringing in 1,836,000 barrels per day. According to CEIC Data, the Netherlands imported 1,059,927 barrels per day in December 2021 (Yahoo Finance, 2023).

Despite having local refineries, Canada, a big oil producer, nonetheless imports oil. Canada produced 3.8 million barrels per day in 2014, exported 2.9 million barrels per day, delivered 1.2 million barrels per day to domestic refineries, and imported 0.7 million barrels per day to domestic refineries, according to Canadian government data. In 2017, Mexico exported 1,214,000 barrels of crude oil, a large portion of which went to refineries in the South of the United States. As of January 2021, Brazil is believed to have 12.7 billion barrels of proven oil reserves, and during the previous several decades, the nation has expanded more of its potential, particularly offshore.

The price movement of Brent oil in dollar terms between 29 July 2016 and 14 February 2023 is shown in Figure 1.

Fig.1. Brent Crude Oil Price, In Dollars, From 29 July 2016 To 14 February 2023

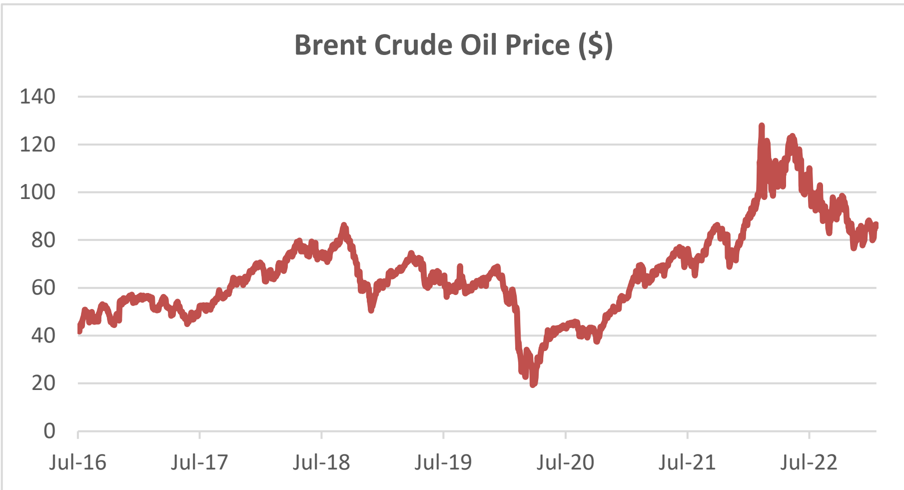

Figure 2 plots the stock market indices of oil-importing and exporting countries over time.

Fig.2. Stock Market Indices

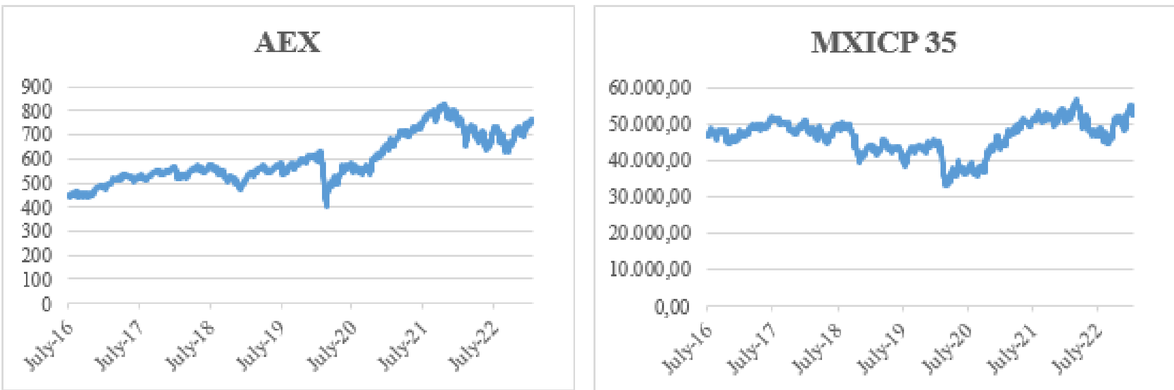

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Fig.2. Continue.

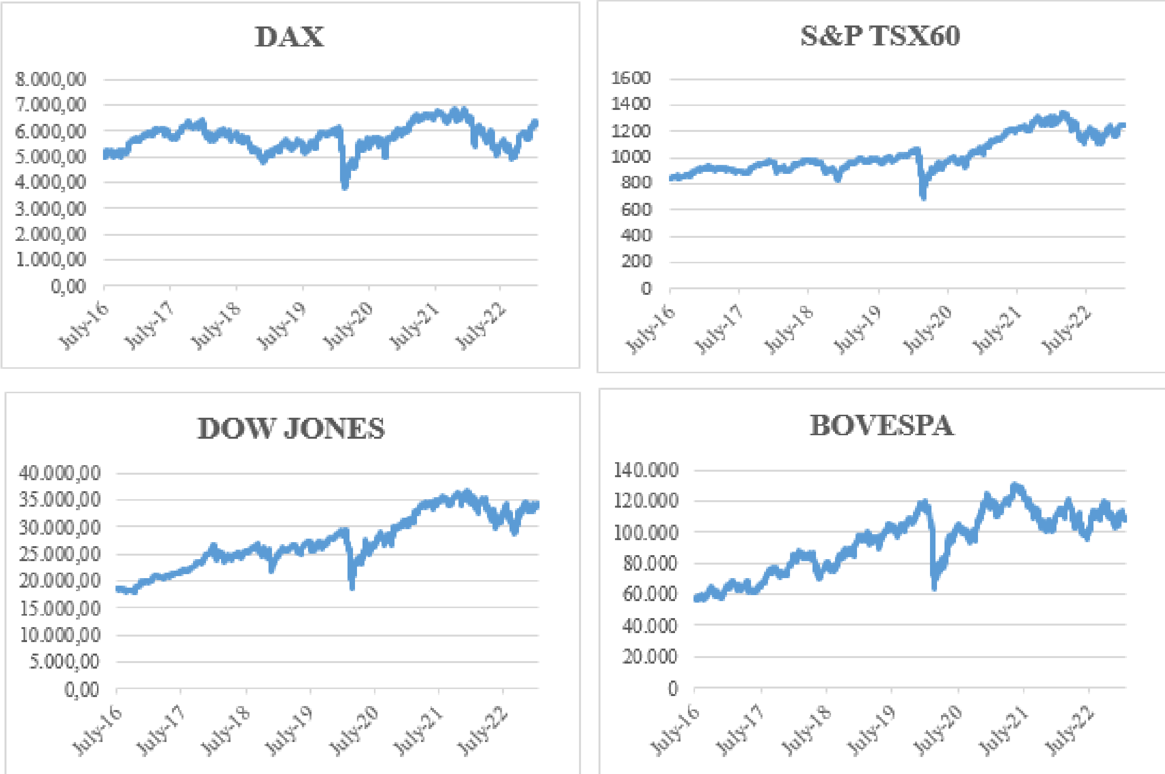


Table 1 gives the descriptive statistics of stock market prices and Brent oil prices.

Table 1. Descriptive statistics of returns

	BRENT OIL	AEX	DAX	DOW JONES	MXICP 35	S&P TSX60	BOVESPA
Mean	0.00076203	0.00031479	0.00023958	0.00037635	0.00007798	0.00021367	0.00039379
Maximum	0.3196337	0.08590747	0.1041429	0.1076433	0.04180595	0.1129453	0.1302228
Minimum	-0.2822061	-0.1137584	-0.1305486	-0.1384181	-0.06638094	-0.131758	-0.1599303
Std. Deviation	0.03088259	0.0109201	0.01230551	0.01230909	0.01035234	0.01032918	0.01629022
Skewness	0.05730242	-0.8954873	-0.6621324	-1.026644	-0.473647	-1.888431	-1.39075
Kurtosis	26.2929	12.3564	14.2413	22.31307	3.672783	45.14707	17.77277
Jarque-Bera	47657	10925	14216	34530	990.89	140620	22027
Testi	($p<0.05$)	($p<0.05$)	($p<0.05$)	($p<0.05$)	($p<0.05$)	($p<0.05$)	($p<0.05$)
ARCH-LM	-	1672.5	1577.2	1611.6	1073.5	2158	2015.9*

Table 1 summarizes a multivariate time series analysis performed with the ARCH (Autoregressive Conditional Heteroscedasticity) model. According to this output, it cannot be concluded that the series can be modeled with ARCH group models. This output only shows the result of the ARCH test and indicates that the residues are heteroscedastic. The presence of heteroscedasticity does not require the use of ARCH models; instead, different methods can be used to solve the problem of heteroscedasticity. ARCH models can be used as an option to address the problem of heteroscedasticity, but this output does not indicate that this model should be used.

This output also summarizes the Jarque-Bera test result. This test is used to test whether a data set is normally distributed. Since the results of the Jarque-Bera test are greater than five and $p < 0.05$, the null hypothesis is rejected, and it is determined that the return data do not fit the Normal distribution.

The study aims to observe the impact of COVID-19 on the relationship between oil prices and stock market prices of countries. Since countries have different dates of restrictions, a distinction is made between before and after the date of the first case. In this study, conducted between July 29, 2016, and February 14, 2023, the period before and after COVID-19 is determined based on December 1, 2019.

The ARCH-LM statistic is used to test whether the residuals of the model have constant variance by default. According to the test result ($p<0.05$), the null hypothesis is rejected, and it is concluded that the residuals of the model are heteroscedastic, reinforcing that it did not have constant variance by default.

In this study, the ADF (Augmented Dickey-Fuller) unit root test is used to investigate whether the series are stationary. According to the ADF unit root test, the hypotheses are as follows.

H_0: The series is not stationary. (Contains unit root)

H_1: The series is stationary. (Does not contain unit root)

The null hypothesis is rejected if it is greater than the Mac-Kinnon critical values at 1%, 5% and 10% significance levels and if p<0.05. Thus, it is accepted that the series does not contain a unit root and is stationary. Unit root test results are given in Table 2.

Table 2. ADF Unit Root Test Results

		Level		**Lag-1**		
Variables	***Model***	***ADF stats.***	***p***	***ADF stats.***	***p***	***MacKinnon statistics***
	Fixed and Trendless Model	-1.174825	0.5043072	-28.8968	<0,001	-1,943
OIL	*Fixed Term Model*	-2.162489	0.5095298	-29.24676	<0,001	-2,881
	Fixed Term and Trend Model	-2.159733	0.5106964	-24.66124	<0,001	-3,442
	Fixed and Trendless Model	-1.549305	0.3457775	-28.24716	<0,001	-1,943
AEX	*Fixed Term Model*	-2.539011	0.3501354	-28.26794	<0,001	-2,881
	Fixed Term and Trend Model	-2.614711	0.3180892	-23.37204	<0,001	-3,441
	Fixed and Trendless Model	-1.779784	0.2482084	-28.12354	<0,001	-1,943
DAX	*Fixed Term Model*	-2.734087	0.2675534	-28.12515	<0,001	-2,881
	Fixed Term and Trend Model	-2.856683	0.2156546	-22.9112	<0,001	-3,441
	Fixed and Trendless Model	-1.199409	0.08801308	-27.90988	<0,001	-1,943
DOW JONES	*Fixed Term Model*	-2.827699	0.2279251	-27.93783	<0,001	-2,881
	Fixed Term and Trend Model	-3.085744	0.1186863	-22.87703	<0,001	-3,441
	Fixed and Trendless Model	-1.842854	0.6448414	-28.85262	<0,001	-1,943
MXICP 35	*Fixed Term Model*	-1.957654	0.596243	-28.64772	<0,001	-2,881
	Fixed Term and Trend Model	-1.881151	0.6286289	-24.27676	<0,001	-3,441
	Fixed and Trendless Model	-1.618008	0.3166938	-27.55308	<0,001	-1,943
S&P TSX60	*Fixed Term Model*	-2.399229	0.4093099	-27.26214	<0,001	-2,881
	Fixed Term and Trend Model	-2.597038	0.3255712	-21.37711	<0,001	-3,441
	Fixed and Trendless Model	-1.843517	0.2212292	-29.03261	<0,001	-1,943
BOVESPA	*Fixed Term Model*	-2.516012	0.3598722	-29.00242	<0,001	-2,881
	Fixed Term and Trend Model	-2.630344	0.311472	-22.79327	<0,001	-3,441

When Table 2 is examined, the null hypothesis cannot be rejected since the absolute value of the τ statistics obtained for the variables at the 5% significance level, according to the level ADF test statistics obtained for the three models in all return series, is smaller than the MacKinnon statistics. Similarly, the probability value determined for the null hypothesis tested as "there is a unit root" or "the series is not stationary" is found to be significant at the 5% significance level, and it is decided that the related series for these variables are not stationary in the level case. In this case, the stationarity test is applied again by taking the first-order differences of the variables.

According to the ADF results obtained by applying the first-lag operator in Table 2, it is determined that the ADF unit root test statistic for all models is significant at the 5% significance level and the first-lag operator of the variables of interest is stationary, that is, there is no unit root. In this case, it is seen that each of the variables is not stationary at the level but provides the stationarity property for the first-lag values. Therefore, it is decided that the variables are first-order integrated and that there may be a long-term relationship between the variables.

Phillips-Perron test is also applied along with ADF to determine the stationarity of the series. The null hypothesis is rejected if p<0.05. Thus, it is accepted that the series does not contain a unit root and is stationary. Unit root results according to the Phillips-Perron test are given in Table 3.

Table 3. Phillips-Perron Unit Root Test Results

		Level		Lag-1	
Variables	*Model*	*t-stats.*	*p*	*t-stats.*	*p*
	Fixed and Trendless Model	0.177	0.732	-1539	<0,001
OIL	*Fixed Term Model*	-5.9	0.411	-1538	<0,001
	Fixed Term and Trend Model	-8.25	0.565	-1538	<0,001
	Fixed and Trendless Model	0.416	0.785	-1758	<0,001
AEX	*Fixed Term Model*	-3.72	0.573	-1755	<0,001
	Fixed Term and Trend Model	-14.4	0.271	-1755	<0,001
	Fixed and Trendless Model	0.265	0.751	-1779	<0,001
DAX	*Fixed Term Model*	-9.4	0.209	-1778	<0,001
	Fixed Term and Trend Model	-16.8	0.164	-1778	<0,001
	Fixed and Trendless Model	0.444	0.791	-1919	<0,001
DOW JONES	*Fixed Term Model*	-3.54	0.594	-1915	<0,001
	Fixed Term and Trend Model	-18.6	0.0957	-1915	<0,001
	Fixed and Trendless Model	0.0646	0.707	-1509	<0,001
MXICP 35	*Fixed Term Model*	-7.46	0.321	-1509	<0,001
	Fixed Term and Trend Model	-7.79	0.599	-1508	<0,001
	Fixed and Trendless Model	0.286	0.756	-1980	<0,001
S&P TSX60	*Fixed Term Model*	-4.13	0.527	-1978	<0,001
	Fixed Term and Trend Model	-14.9	0.248	-1978	<0,001
	Fixed and Trendless Model	0.29	0.757	-1923	<0,001
BOVESPA	*Fixed Term Model*	-5.61	0.428	-1921	<0,001
	Fixed Term and Trend Model	-16.3	0.189	-1920	<0,001

When the probability values obtained at the level are examined, it can be said that the null hypothesis cannot be rejected, and the series is not stationary. However, according to the Phillips-Perron test results obtained by applying the first-lag operator, it is determined that all variables are stationary at the first-lag operator; that is, there is no unit root. In this case, it is seen that each of the variables is not stationary at level but provides stationarity for the first-lag values. For this reason, it is decided that the variables are first-order integrated and that there may be a long-term relationship between the variables.

With the univariate GARCH modeling for each variable, the volatility persistence from the variables' own lagged values is examined. For each variable, the α parameter shows the effect of the variables' own volatility shock, while the β parameter is the expression of the permanence of the shock. In order for the hypothesis of volatility persistence to be accepted, the condition $\alpha + \beta < 1$ must be met. DCC model findings before and after COVID-19 are given in Table 4.

Table 4. DCC Model Findings

	BEFORE COVID-19				AFTER COVID-19			
	Estimate	Std. Error	t-value	Pr(>|t|)	Estimate	Std. Error	t-value	Pr(>|t|)
$\boldsymbol{\mu_{B.OIL}}$	0.000692	0.000670	1.03302	0.30159	0.002538	0.000883	2.8736	0.004059
$\boldsymbol{\Omega_{B.OIL}}$	0.000010	0.000001	8.33197	0.00000	0.000023	0.000013	1.8216	0.068515
$\boldsymbol{\alpha_{B.OIL}}$	0.049115	0.003279	14.97775	0.00000	0.179093	0.071438	2.5070	0.012177
$\boldsymbol{\beta_{B.OIL}}$	0.920545	0.009308	98.89744	0.00000	0.819907	0.046224	17.7375	0.000000
$\boldsymbol{\mu_{AEX}}$	0.000689	0.000270	2.54997	0.010773	0.000677	0.000776	0.87251	0.382932
$\boldsymbol{\Omega_{AEX}}$	0.000010	0.000000	51.67080	0.000000	0.000008	0.000003	2.36865	0.017853
$\boldsymbol{\alpha_{AEX}}$	0.149978	0.022001	6.81675	0.000000	0.180698	0.041314	4.37378	0.000012
$\boldsymbol{\beta_{AEX}}$	0.634000	0.040676	15.58659	0.000000	0.779531	0.056492	13.79898	0.000000
$\boldsymbol{DCC_{\alpha}}$	0.004366	0.007390	0.59072	0.554707	0.072906	0.032560	2.23914	0.025147
$\boldsymbol{DCC_{\beta}}$	0.982078	0.007833	125.37750	0.000000	0.132797	0.130771	1.01549	0.309874
$\boldsymbol{\mu_{DAX}}$	0.000356	0.000334	1.06413	0.28727	0.000604	0.000423	1.4263	0.153793
$\boldsymbol{\Omega_{DAX}}$	0.000001	0.000002	0.57184	0.56743	0.000010	0.000004	2.4962	0.012554
$\boldsymbol{\alpha_{DAX}}$	0.026259	0.021388	1.22773	0.21955	0.166873	0.050895	3.2788	0.001043
$\boldsymbol{\beta_{DAX}}$	0.953504	0.012681	75.19138	0.00000	0.796274	0.041541	19.1686	0.000000

Table 4. Continue.

DCC_α	0.000001	0.001064	0.000047	0.99996	0.030025	0.021944	1.3683	0.171228
DCC_β	0.915514	0.690775	1.325344	0.18506	0.922471	0.056831	16.2318	0.000000
μ_{DJ}	0.000910	0.000236	3.8624	0.000112	0.000734	0.000376	1.9538	0.050726
Ω_{DJ}	0.000002	0.000003	0.8763	0.380865	0.000009	0.000005	1.7774	0.075508
α_{DJ}	0.138814	0.042179	3.2911	0.000998	0.292461	0.054531	5.3632	0.000000
β_{DJ}	0.820971	0.065632	12.5086	0.000000	0.676460	0.086848	7.7890	0.000000
DCC_α	0.037240	0.029833	1.2483	0.211932	0.089261	0.028308	3.1532	0.001615
DCC_β	0.712312	0.105681	6.7402	0.000000	0.884458	0.045411	19.4770	0.000000
μ_{MXICP}	0.000072	0.000278	0.25920	0.795479	0.000374	0.000422	0.88541	0.375933
Ω_{MXICP}	0.000005	0.000004	1.30207	0.192894	0.000005	0.000008	0.67696	0.498432
α_{MXICP}	0.202556	0.041989	4.82402	0.000001	0.113261	0.025042	4.52284	0.000006
β_{MXICP}	0.749115	0.059558	12.57783	0.000000	0.850216	0.049334	17.23378	0.000000
DCC_α	0.049137	0.076569	0.64173	0.521047	0.077109	0.045891	1.68026	0.092906
DCC_β	0.457642	1.229948	0.37208	0.709831	0.359830	0.169888	2.11805	0.034171
μ_{TSX60}	0.000257	0.000211	1.220629	0.222227	0.000862	0.000277	3.1113	0.001862
Ω_{TSX60}	0.000001	0.000001	1.489633	0.136321	0.000006	0.000004	1.7952	0.072626
α_{TSX60}	0.085464	0.032288	2.646948	0.008122	0.366260	0.103640	3.5340	0.000409
β_{TSX60}	0.873750	0.030056	29.071223	0.000000	0.619308	0.110137	5.6231	0.000000
DCC_α	0.000000	0.000041	0.000401	0.999680	0.043701	0.026113	1.6735	0.094227
DCC_β	0.924067	0.242965	3.803284	0.000143	0.802873	0.082415	9.7418	0.000000
μ_{BVSP}	0.000916	0.000558	1.64372	0.10023	0.000618	0.000586	1.0540	0.291883
Ω_{BVSP}	0.000023	0.000023	0.97983	0.32717	0.000018	0.000014	1.3214	0.186374
α_{BVSP}	0.054970	0.043855	1.25346	0.21004	0.159429	0.070621	2.2575	0.023975
β_{BVSP}	0.816057	0.149908	5.44372	0.00000	0.780463	0.099993	7.8052	0.000000
DCC_α	0.017961	0.019486	0.92170	0.35668	0.039466	0.027480	1.4362	0.150946
DCC_β	0.928395	0.023638	39.27472	0.00000	0.838947	0.118848	7.0590	0.000000

The results in Table 4 show that the volatility shock has an effect of 4.915% ($\alpha_{b.oil}$) and the volatility persistence is 92.0545% ($\beta_{b.oil}$) for the Brent Oil ARCH effect. The value of $\alpha + \beta$, which represents the persistence of volatility in Brent Oil, is 0.96966<1. After COVID-19, the volatility shock impact in Brent Oil is 17.9093% ($\alpha_{b.oil}$) and the volatility persistence is 81.9907% ($\beta_{b.oil}$), according to the ARCH effect. The volatility persistence in Brent Oil is shown by the $\alpha + \beta$ value, which is 0.999<1. From this vantage point, it is assumed that volatility in the Brent Oil return series will endure. Put differently, it is acknowledged that volatility in this market has a lasting impact.

The ARCH effect, or volatility shock effect, is 14.9978% (α_{AEX}), and volatility persistence is 63.4% (β_{AEX}) in the AEX Index. The AEX Index's persistence of volatility is expressed by $\alpha + \beta$, and its value is 0.783978<1. Following the COVID-19 pandemic, the AEX Index experienced an ARCH impact of 18.0698% (α_{AEX}) for volatility shocks and 77.9531% (β_{AEX}) for volatility persistence. It is found that the value of $\alpha + \beta$, which indicates the volatility persistence in the AEX Index, is 0.960229<1. From this vantage point, it is agreed that the AEX Index return series exhibits persistent volatility. Put differently, it is acknowledged that volatility in this market has a lasting impact.

The results show that the DAX Index has an ARCH impact, or, to put it another way, that the volatility shock has an effect of 0.26259% (α_{DAX}) and the volatility persistence is 95.3504% (β_{DAX}). The DAX Index's volatility persistence is expressed by the $\alpha + \beta$ value, which is 0.979763<1. Following the COVID-19 pandemic, the DAX Index experienced an ARCH impact of 16.6873% (α_{DAX}) for volatility shocks and 79.6274% (β_{DAX}) for volatility persistence. The DAX Index's persistence of volatility is expressed by the value of $\alpha + \beta$, which is 0.963147<1. From this vantage point, it is agreed that the AEX Index return series exhibits persistent volatility. Put differently, it is acknowledged that volatility in this market has a lasting impact.

The results show that the Dow Jones Index exhibits an ARCH effect, or, to put it another way, a volatility shock effect of 13.8814% (α_{DJ}) and volatility persistence of 82.0971% (β_{DJ}). The value of $\alpha + \beta$, which indicates how long volatility has persisted in the Dow Jones Index, is 0.959785<1. Following the COVID-19 pandemic, the Dow Jones Index experienced an ARCH impact of 29.2461% (α_{DJ}) for volatility shocks and 67.6460% (β_{DJ}) for volatility persistence. The value of $\alpha + \beta$, which indicates how long volatility has persisted in the Dow Jones Index, is 0.968921<1. From this vantage point, it is agreed that there is continuous volatility in the Dow Jones Index return series. Put differently, it is acknowledged that volatility in this market has a lasting impact.

Table 4 shows that for the MXICP35 Index, the volatility persistence is 74.915% (β_{MX}), and the effect of the volatility shock is 20.2556 (α_{MX}). This is known as the ARCH effect. It is found that the MXICP35 Index's persistence of volatility is expressed by the $\alpha + \beta$ value, which is 0.951671<1. Following the COVID-19 pandemic, the MXICP35 Index experienced an ARCH impact of 11.3261 (α_{MX}) for the volatility shock and 85.0216% (β_{MX}) for the volatility persistence. The persistence of volatility is expressed by $\alpha + \beta$ in the MXICP35 Index, and its value is 0.963477<1. From this vantage point, it is acknowledged that volatility in the MXICP35 Index return series will remain. Put differently, it is acknowledged that volatility in this market has a lasting impact.

The ARCH effect, or volatility shock effect, is 8.5464% (α_{TSX}), and volatility persistence is 87.3750% (β_{TSX}) for the S&P TSX60 Index. The value of $\alpha + \beta$ in the MXICP35 Index, which represents the volatility's persistence, is 0.959214<1. Following the COVID-19 pandemic, the S&P TSX60 Index experienced the ARCH effect. This means that the volatility shock had an effect of 36.6260% (α_{TSX}), and the volatility persistence is 61.9308% (β_{TSX}). The value of $\alpha + \beta$ of the S&P TSX60 Index, which represents the volatility's persistence, is 0.985568<1. From this vantage point, it is agreed that the S&P TSX60 Index return series exhibits persistent volatility. Put differently, it is acknowledged that volatility in this market has a lasting impact.

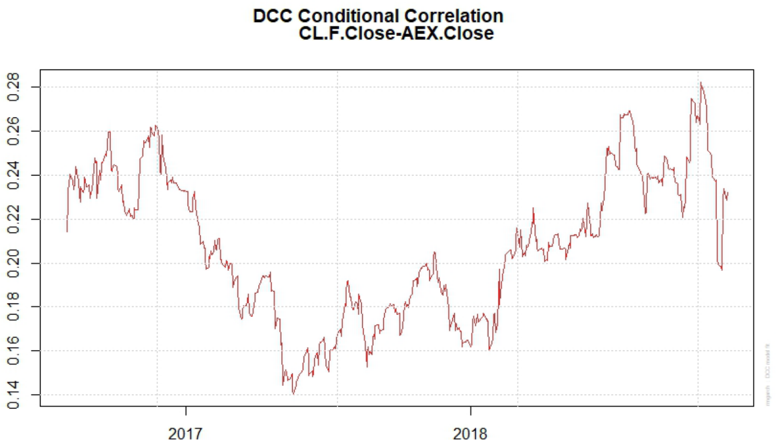
The results in Table 4 show that the volatility shock has an effect of 5.4970% (α_{BP}), and the volatility persistence is 81.6057% (β_{BP}) in the BOVESPA Index, which is known as the ARCH effect. The MXICP35 Index's coefficient of persistence of volatility, $\alpha + \beta$, is 0.871027<1. In the BOVESPA Index, the ARCH effect for the post-COVID-19 period is 15.9429% (α_{BP}) for the volatility shock and 78.0463% (β_{BP}) for the volatility persistence. The value of $\alpha + \beta$ of the BOVESPA Index, which represents the volatility's persistence, is 0.939892<1. From this vantage point, it is acknowledged that there is volatility in the return series of the BOVESPA Index. Put differently, it is acknowledged that volatility in this market has a lasting impact.

When the parameters of dynamic conditional correlation are examined in Table 4, DCCα expresses the effect of past shocks on current conditional correlations, while DCCβ captures the effect of past correlations. The statistical significance of these parameters means that the conditional correlations are not constant. When DCC parameters of binary models created with Brent oil are examined, it is seen that correlations are not constant in all binary structures. When DCC parameters are examined, DCCα ≈ 0 and DCCβ coefficient for all structures are greater than zero, and the sum of the two is less than 1. Therefore, the results are meaningful and in accordance with the theoretical ground. Based on the DCC model results, it is observed that the correlation of Brent oil with the indices included in the research changed over time.

During the post-COVID-19 period, the pattern shows that the correlation coefficient for all stock markets is still in the positive area.

The graphs obtained from the time-varying correlation coefficients calculated for the pre-COVID-19 period between the stock market index and Brent oil prices among the three oil-importing countries are presented in Figure 3.

Fig.3. Dynamic Correlation Between The Lagged Crude Oil Price And Three Oil-Importing Nations In The Stock Market Index Before COVID-19



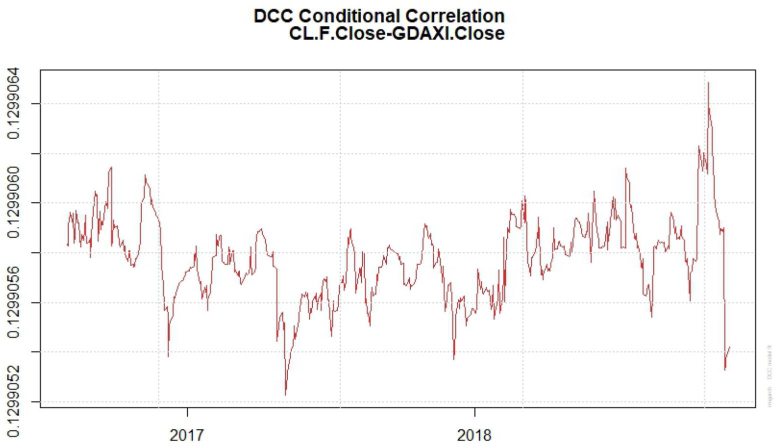
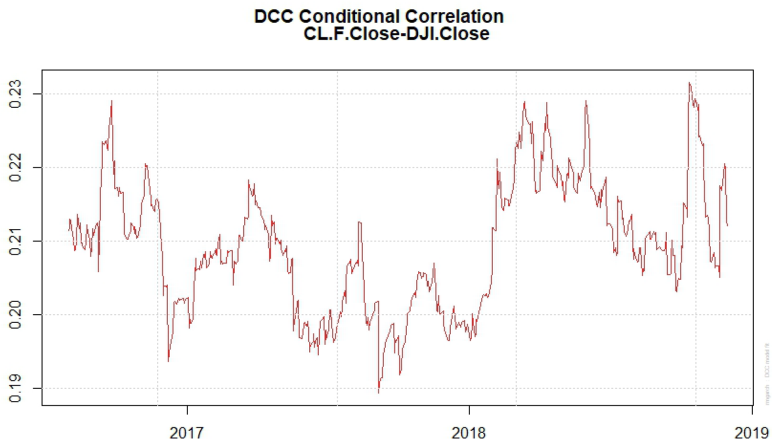
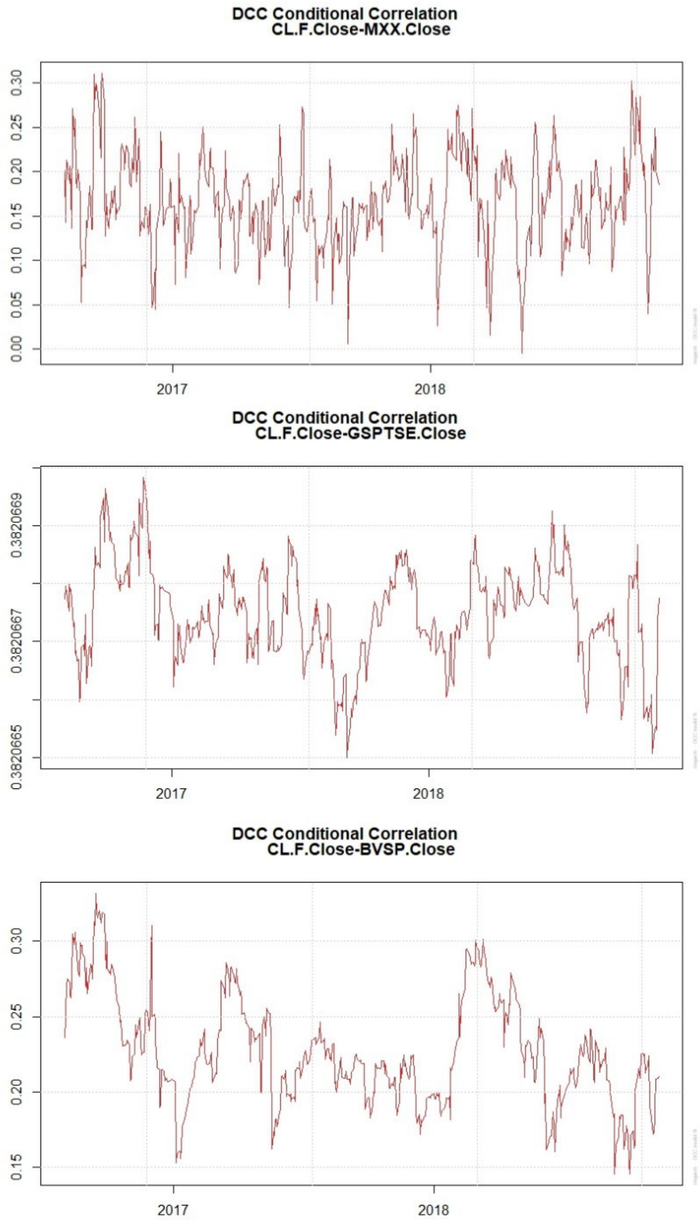


Fig.3. Continue.



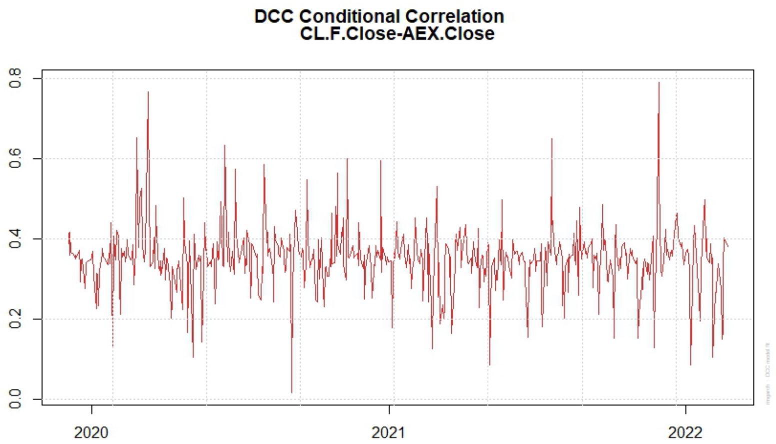
The graphs obtained from the time-varying correlation coefficients calculated for the pre-COVID-19 period between the stock market index and Brent oil prices among the three oil-exporting countries are presented in Figure 4.

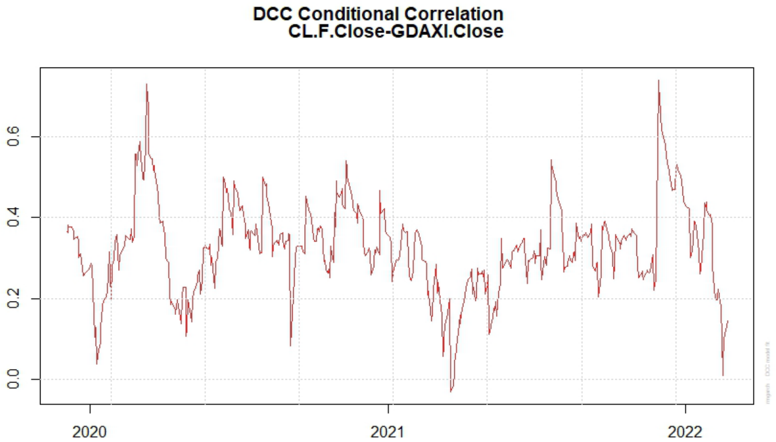
Fig.4. Dynamic Correlation Between The Lagged Crude Oil Price And Three Oil-Exporting Nations In The Stock Market Index Before COVID-19

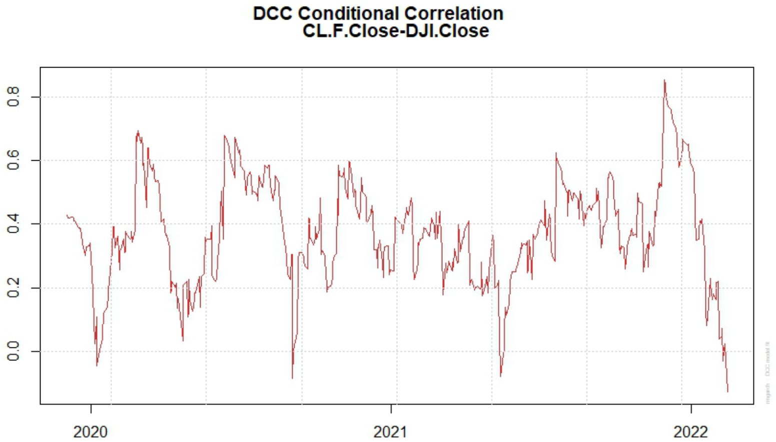


The graphs obtained from the time-varying correlation coefficients calculated for the post-COVID-19 period between the stock market index and Brent oil prices among the three oil-importing countries are presented in Figure 3.

Fig.5. Dynamic Correlation Between The Lagged Crude Oil Price And Three Oil-Exporting Nations In The Stock Market Index After COVID-19







The graphs obtained from the time-varying correlation coefficients calculated for the post-COVID-19 period between the stock market index and Brent oil prices among the three oil-exporting countries are presented in Figure 6.

Fig.6. Dynamic Correlation Between The Lagged Crude Oil Price And Three Oil-Exporting Nations In The Stock Market Index After COVID-19

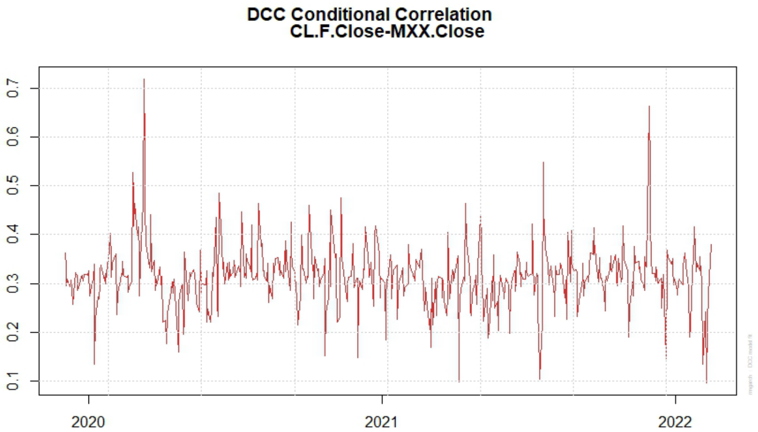
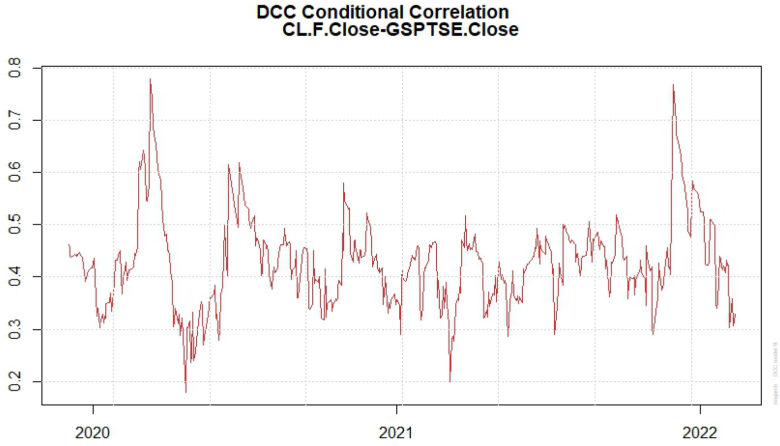
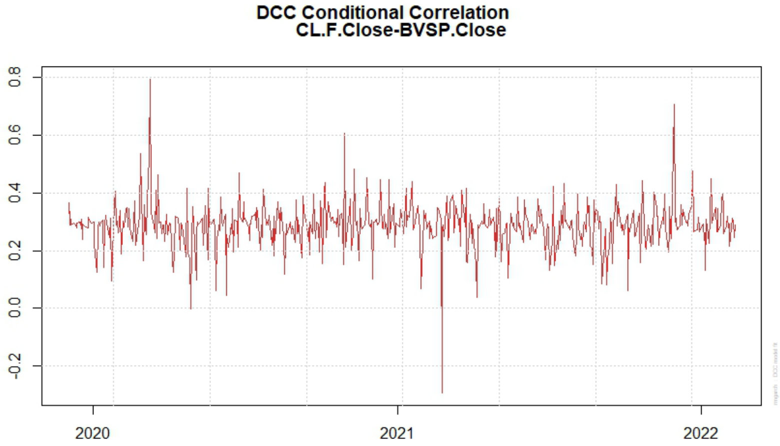


Fig.6. Continue.





Correlations between the indices and Brent oil are given in Table 5.

Table 5. Correlation results

	BEFORE COVID-19		AFTER COVID-19	
	ρ	Pr(>|t|)	ρ	Pr(>|t|)
AEX	0.2419	0.0000	0.4304	0.0000
DAX	0.1296	0.0000	0.3415	0.0000
DOW JONES	0.1985	0.0000	0.3603	0.0000
MXICP 35	0.3420	0.0000	0.3936	0.0000
S&P TSX60	0.3762	0.0000	0.4503	0.0000
BOVESPA	0.2415	0.0000	0.2931	0.0000

It is determined that all correlation values obtained are statistically significant ($sig < \alpha = 0{,}05$). An increase in correlation is observed after COVID-19 for both oil-exporting and oil-importing countries. A positive dramatic increase is observed in the relationship between the indices of oil importing countries (AEX, DAX, Dow Jones) and Brent oil after COVID-19. Despite this, although an increase is observed for the indices of oil-exporting countries (MXICP 35, S&P TSX 60, BOVESPA), we cannot talk about a dramatic increase like the indices of oil-importing countries.

3. Discussion

The study examines the impact of unexpected changes (shocks) in volatility (how much prices move up and down) due to COVID-19 on six financial indices along with oil prices. It has been determined that all variables show signs of persistent volatility. This means that unexpected changes in volatility tend to have a lasting impact on prices in these markets. In other words, if the market becomes more volatile, it tends to remain volatile for a while.

When volatility persistence is examined from the variables' own lagged values with univariate GARCH modeling for each variable, volatility shocks in Brent oil have a greater impact after COVID-19 than before. This shows us that the fluctuation in oil prices has become more pronounced during the epidemic period.

When volatility shocks are examined for oil-importing country indices (AEX, DAX, Dow Jones), it is found that they have a greater impact after COVID-19 than before. This indicates a significant increase in market fluctuations during the COVID-19 period.

On the other hand, when oil exporting countries are examined, a striking situation emerges. It has been determined that the effect of volatility shocks on the MXICP35 index is smaller after COVID-19 than before. This suggests a decrease in market fluctuations during the pandemic period. Volatility shocks have been found to have a greater impact on the S&P TSX60 and BOVESPA indices after COVID-19 than before. It points to a significant increase in market volatility after the COVID-19 period for both markets.

All markets give a value less than 1 for the sum of α and β; this means that volatility will decrease over time, but the shock effects will continue for a while. This could mean that any shock, such as the COVID-19 pandemic, could lead to long-term instability in these markets.

The study reveals that all correlation values we obtained for stock markets (indexes) and Brent oil are statistically significant, meaning that the relationships we found are not due to chance.

Before COVID-19, a connection between stock markets and oil prices is identified, but this connection is not very strong.

An increase in correlation has been seen for both oil-exporting and oil-importing countries since the onset of COVID-19. This means that oil prices and stock market movements in the studied countries have become more aligned during the pandemic.

Interestingly, following COVID-19, a striking increase has been observed in the correlation between Brent oil prices and the stock market indices of oil-importing countries (AEX, DAX, Dow Jones). This shows that the stock markets in these countries have become much more sensitive to changes in oil prices during the pandemic period.

For oil-exporting countries (MXICP 35, S&P TSX 60, BOVESPA), an increase in correlation is determined after COVID-19, but the increase is not as dramatic as in oil-importing countries. This suggests that stock markets in these countries have become more sensitive to changes in oil prices during the epidemic, but the effect is not as pronounced as in oil-importing countries.

According to the work of (Sharif et al., 2020), COVID-19 has been expressed as an economic crisis with varying impacts. It has been stated that the decline in oil, along with COVID-19, had the strongest impact on the US stock markets. It was observed that oil prices led the US market at both low and high frequencies throughout the observation period. The study supports the relationship between the shock effect of COVID-19 and oil prices and stock market indices. The study emphasizes both the crisis situation of COVID-19 and the relationship between oil prices and markets.

Zhang & Hamori (2021)'s study emphasizes that the impact of COVID-19 on the markets is uncertain in the short and long term. However, it has been stated that the impact of COVID-19 on the markets exceeds the 2008 financial crisis. It is emphasized in the study that the impact of COVID-19 creates an unprecedented level of risk, such as the collapse of oil prices and the triggering of the circuit breaker in the US stock market four times, causing investors to suffer heavy losses in a short time. This result is consistent with the emphasis on correlation in our study. In this context, it supports the results of the United States stock market, which we also work on.

On the other hand, F. Zhang et al.'s (2021) study evaluates whether COVID-19 affected the relationship between oil prices and stock return forecasts in Japan. It shows that the impact of oil prices on stock returns decreased by around 89.5% due to COVID-19. This finding is not compatible with the result obtained in our study. However, the differences in the time periods and countries of the two studies are noteworthy. Therefore, in-depth research on this subject should continue.

In conclusion, the study shows that all of the financial markets analyzed have a permanent effect of volatility. This result implies that investors should consider the risk associated with volatility while making investment decisions. Furthermore, policymakers should monitor the volatility and take necessary measures to minimize the risk associated with it.

The study's findings provide useful insights for both investors and policymakers. Investors can use this information to better understand the risks associated with different financial markets and make informed investment decisions. They should carefully consider the level of volatility in each market and diversify their portfolios to minimize risk. Policymakers, on the other hand, can use these results to develop appropriate policies to manage volatility in financial markets. By monitoring volatility and taking necessary measures, such as implementing regulations and safeguards, they can help ensure that financial markets remain stable and secure.

It is important to note that the study's results are based on historical data and may not accurately predict future market behavior. Therefore, investors and policymakers should continue to monitor volatility and adjust their strategies accordingly. Nonetheless, this study provides valuable information on the persistence of volatility in financial markets and highlights the need for careful risk management strategies. By doing so, investors and policymakers can work together to create a more stable and resilient financial system.

Conclusion and Policy Implications

Even though the effects of oil price on macroeconomic variables have been extensively studied, the literature on the relationship between the stock market and oil prices is still growing. In this study, a quantitative technique called Dynamic Conditional

Correlation asymmetric GARCH or DCC GARCH-GJR, which has not been applied before, is used to investigate the time-varying correlation between oil and stock market prices, taking into account the origin of oil.

With increased volatility during the pandemic period, it is clear that shocks have significant and lasting effects. It has been observed that volatility shocks in Brent oil and stock market indices of oil-importing countries such as AEX, DAX, and Dow Jones have a greater impact after COVID-19. However, the effects appear to be less severe for some oil-exporting countries.

Interestingly, this study finds an increasing correlation between oil prices and stock market movements during the pandemic. This shows that changes in oil prices directly affect financial markets and are, therefore, more aligned with them. Increasing sensitivity to changes in oil prices in both oil-importing and exporting countries highlights the need for careful observation and management of market fluctuations.

These findings underscore the need for investors to be careful when dealing with volatile markets. It is crucial to consider the risks associated with volatility when making investment decisions. The study also provides direction to policymakers who need to manage volatility in financial markets through regulations and measures, thereby promoting stability.

As a result, ongoing volatility in financial markets requires careful risk management strategies. This study highlights the potential for long-term instability in these markets due to significant shocks, such as the COVID-19 pandemic. Therefore, a collaborative effort between investors and policymakers is required to develop a more stable and resilient financial system.

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The author has declared that there are no other contributors.

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