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Return And Volatility Spillover Between Energy Commodities: Evidence From the VAR-EGARCH Model[1]

Enerji Emtiaları Arasında Getiri ve Volatilite Yayılımı: VAR-EGARCH Modelinden Kanıtlar

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Ö Z

Bu araştırmanın amacı enerji emtiaları arasında getiri ve volatilite yayılımı olup olmadığını incelemektir. Farklı makroekonomik gelişmeler neticesi varlık fiyatlarında meydana gelen getiri oynaklıkları emtialar arasında yayılım göstererek birbirlerinin getirilerini de etkileyebilmektedir. Enerji emtialarının fiyatlarını etkileyen unsurların ve aralarındaki yayılımın tespiti özellikle yatırım yapmak isteyenler ve enerji piyasası ile ilgilenenler açısından incelenmeye değer bulunmaktadır. Araştırma kapsamında 01.01.2008-31.12.2020 tarihleri arasındaki Brent Petrol, Heating Oil, Natural Gas ve WTI ham petrol verileri VAR-EGARCH yöntemiyle değerlendirilmiştir. Araştırma sonucunda enerji emtialarına ait getirilerin kısa dönemli etkileşim halinde olduğu bilgi şoklarının getiri ve volatilitede çoklu ve asimetrik olarak yayıldığı görülmüştür. Doğalgaz getiri serisinin diğer emtiaların fiyatlarından etkilendiği fakat kendisinin hiçbir enerji emtiasını etkilemediği ayrıca tespit edilmiştir. Volatilite yayılımında ise ısıtma yağından doğalgaz serilerine tek taraflı diğer emtialar arasında karşılıklı yayılım olduğu sonucuna varılmıştır.

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A B S T R A C T

This study aims to examine whether there is a return and volatility spillover among energy commodities. As a result of different macroeconomic developments, return volatility in asset prices can spillover among commodities and affect each other's returns. The determination of the factors affecting the prices of energy commodities and the spillover among them is worth examining, especially for those who invest and are interested in the energy market. Within the scope of the study, the data regarding Brent Oil, Heating Oil, Natural Gas, and WTI between 01.01.2008-31.12.2020 are evaluated by VAR-EGARCH method. The results demonstrate that the information shocks, in which the returns of energy commodities interact in the short-term, spillover multidirectionally and asymmetrically in returns and volatility. It is determined that the natural gas return series is affected by the prices of other commodities, but it does not affect any energy commodities. As for the volatility spillover, there is unidirectional spillover from heating oil to natural gas series, but there is a multidirectional spillover among other commodities.

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Introduction

Energy is a key source of economic growth, as it is the basic input of many production and consumption activities in almost every field. At the same time, it is one of the most important inputs of economic development. Energy use affects economic productivity and industrial growth, and forms the basis of the functioning of the modern economies (Asghar, 2008: 167). Energy commodities and energy market elements are important and worth researching in terms of being an important part of the economy and affecting the areas and commodities with which they interact. Energy resources are divided into two groups according to their recyclability. Primary sources in this group are oil, coal, natural gas, nuclear, hydraulic, biomass, wave-tide, solar, and wind while secondary sources are electricity, gasoline, diesel, fuel-oil, metallurgical coal, processed coal, gas and liquefied petroleum gas (LPG). As of 2019, the share of primary energy resources was 33.1% oil, 24.2% natural gas, 27% coal, 5.0% renewable energy, 6.4% hydroelectric, and 4.3% nuclear energy (BP,2020:4). In 2020, global energy demand decreased by 4%, the absolute largest since World War II. Energy demand in 2021 has also been significantly affected by the COVID-19 pandemic. As COVID-19 restrictions are lifted and countries' economies recover, energy demand is expected to increase 4.6%, and global energy use is predicted to be 0.5% above pre-COVID-19 levels in 2021 (Global Energy Review, 2021). The sectoral distribution of primary energy consumption in February 2021 was 1,078,964 (trillion btu) in residential areas, 604,937 (trillion btu) in commerce, 1,568,213 (trillion btu) in industry, 1,832,099 (trillion btu) in transportation, and 2,940,011 (trillion btu) in electricity production. In addition, the primary energy source production reached to 83,96336 (trillion btu) in 2020 and 8,03726 (quadrillion btu) as of February 2021 (EIA,2021).

With the rapid developments in commodity markets in recent years, there have been fluctuations in commodity prices. On the other hand, investments have not been affected much by this situation. The main reason for the upward fluctuations in commodity prices in particular is the developments in global demand. Additionally, it is a fact that the global crisis has also affected commodity markets. These fluctuations in the commodity markets have led financial investors in developing and even developed countries to diversify their portfolios and have forced them to seek different alternatives. Increases in the prices of crude oil, which is considered one of the energy commodities, cause significant effects on agriculture, precious metals, and stock markets (Ahmed and Huo, 2020, p.2). Changes in the prices of energy commodities due to a crisis that may affect the energy markets affect both macroeconomic indicators and the countries of which they are producers and consumers in different ways.

One of the most important factors affecting the prices of energy markets is uncertainty. It affects every market in which it is active in many ways. Uncertainty in energy commodities will shape consumer and investor behaviors, and will also spillover to the markets with which it interacts. In their study, Geng et al. (2020) state that natural gas is an indispensable energy source for trade and industry. Uncertainty in economic policies in this area will affect the prices of economic activities of the relevant industries (Geng et al. 2020, p. 3). Oil is a key driver of economic activity and it is widely accepted that stock markets are affected by oil price shocks. Rising oil prices affect the global economy, the transfer of wealth from oil consumers to oil producers, the increase in the cost of production of goods and services, inflation, consumer confidence, and financial markets (Nandha and Faff, 2008, p.986).

There are many factors that affect prices in the oil market, as well as many factors in the natural gas market. These factors can be listed as follows; Natural gas production amount, natural gas storage level, import and export volumes, crises, market-specific factors, seasonal changes, economic growth level, availability of alternative fuels, and prices. Restrictions on natural gas supply infrastructure and natural gas consumers' preference for alternative fuels, short-term increases in demand or decreases in supply cause changes in prices (EIA; 2020). The natural gas market, which is another energy commodity, interacts with the oil market as it is a close substitute goods. The interaction between the oil and natural gas market as well as information and shock transfer has been the subject of many studies. In addition, it is seen that the two markets act together, and this situation is reflected in the prices. Brown and Yücel (2007) suggest the 10 to 1 rule, in which the natural gas price is one-tenth of the crude oil price. A price of $20 per barrel for WTI corresponds to a gas price of $2 per million Btu at Henry Hub, and a price of $50 is considered the natural gas price of $5. Another view is based on the energy content of a barrel of oil. In this case, since a barrel of WTI has a content of 5.825 million btu, some analysts have suggested the 6 to 1 rule, which is calculated as roughly one-sixth of the crude oil price of a million Btu natural gas price. A WTI price of $20 per barrel is a natural gas price of $3.33 per million Btu at Henry Hub, while oil of $50 represents natural gas of $8.33. However, when the relationship between US natural gas prices and WTI is evaluated, it can be said that these two rules are not fully valid. Because the 10 to 1 rule underestimates natural gas prices while the 6 to 1 rule overestimates (Brown and Yücel, 2007, p.3).

The energy market has been significantly affected by the COVID-19 period, which has affected the majority of the world's countries. The epidemic, which started from the city of Wuhan in China in December, was declared as a pandemic by WHO on 12.03.2020 (WHO, 2020). Since the outbreak emerged, many studies have been conducted with different methods to examine its effects on the energy market (Sharif et al. 2020; Narayan, 2020; Kingsly and Henri, 2020; Devpura and Narayan, 2020). Because many countries have implemented strict quarantine policies, economic activities have been adversely affected. It is thought that the negative long-term effects may be an increase in unemployment rates and the closure of many workplaces. There has been an increase in uncertainties in the oil market and stock markets due to COVID-19, but in May 2020, when evaluated together with the global spread of COVID-19, there have been significant changes in the prices of WTI futures with a decrease not seen for a long time in international oil prices. In this case, not only oil demand but also crude oil supply is expected to be affected. Understanding the return and volatility arising from the shocks that will occur is important for investors to avoid risks, especially when investing in this period, and for policy makers to analyze the effects of COVID-19 on the economy and create policies that will improve them (Zhang and Hamori, 2021, p.2). Although similar measures have been taken globally, the energy markets in different countries have been affected differently by the COVID-19 period. Energy importing countries have outperformed energy exporters for the first time in years. There was a decrease in demand for energy exporters and energy importers caused a decrease in import demand due to mobility restrictions, which played an important role in the improvement of energy trade balances (Lukaszewska and Aruga, 2020, p.2). The decrease in prices due to COVID-19 and the downward adjustments in demand reduced oil and gas production in the future by about a quarter. In this case, large oil and gas exporters need to diversify and make new arrangements in order to deal with the negative effects with the least damage. Investment in oil and gas supply decreased by a third compared to 2019. The continuation of COVID-19 and the uncertainty of its future effects mean new price uncertainty and risks related to energy security in the sector (IEA, 2020).

Volatility, which is used to measure uncertainty for financial markets, is a hot topic in financial and financial research. It directs the investment behavior of businesses and individuals. Volatility is often defined as the variance of the rate of return. The correct determination of the volatility in the rate of return is considered to be a proof of the appropriateness of the portfolio selection, the effectiveness of risk management, and the rationality of asset pricing. However, this assumption is actually considered unreasonable, thanks to advances in financial theory and empirical research. Volatility is the tendency of prices to change unexpectedly. At the same time, financial market volatility has a direct impact on macroeconomic indicators and financial stability. Economic risk factors in markets are always considered worldwide. For this reason, research on the volatility of financial markets has become the focus of financial economists and practitioners (Bhowmik and Wang, 2020, p.2-3). To accurately measure volatility, it is crucial to understand the relationship between different energy products, price determinants, and the factors underlying price fluctuations. Crude oil, which is the main component of many substances, constitutes a significant part of the production cost of heating oil and gasoline, so fluctuations in crude oil prices have a significant impact on heating oil and gasoline prices. Therefore, it is necessary to analyze all markets simultaneously to determine the factors affecting volatility. In addition, crude oil is a close substitute for natural gas as an energy source, so it is affected by all kinds of changes in crude oil (Karali and Ramirez, 2014, p.413).

Volatility spillover is the transmission of volatility in one market to the other via a covariance term (Karali and Ramirez, 2014, p.419). The absence of volatility spillover indicates changes in asset- or market-specific fundamentals, and a major shock only increases volatility in that particular asset or market. In contrast, the presence of volatility spillover means that a major shock increases volatility not only in its own asset or market, but also in other assets or markets (Mantalos and Shukur, 2010, p.1474). Volatility spillover is a concept that affects energy and other markets.

In the literature, there are many studies examining the interaction between energy commodities with different commodities, different markets, and different countries. This study differs from other studies in that it examines the spillover of energy commodities and the persistence of shocks with the VAR-EGARCH model and the data includes the COVID-19 period.

In the first part of the study, general explanations about the subject will be made. In the second part, a literature review of studies examining the volatility spread among energy commodities with different methods will be included. In the third part, the data and methodology of the research will be mentioned. In the fourth part, the findings of the analyses will be given. Finally, the results and evaluations will be presented.

Literature Review

Volatility in crude oil prices in energy markets leads to uncertainty, which negatively affects the economy of oil exporting/importing countries. The realization of high prices causes a negative correlation between oil prices and economic activities, an increase in inflation and a subsequent recession in oil-consuming countries. The increase in the sharp fluctuations in oil prices in the last thirty years has made it necessary to examine the concept of volatility (Yang et al.2002, p.107). The volatility interaction between different energy commodities has become a subject of interest in the literature. Volatility spillover has been studied with different techniques in different fields to date. Serra (2011) and Saghaian et al. (2017) examined the volatility spillover between the energy market and the food industry and concluded that there is a volatility spillover between the two markets. Fasanya and Akinbowale (2012) investigated the volatility spillover between crude oil and food prices in Nigeria by applying the method of Diebold and Yılmaz (2012) and found that there is a strong bidirectional volatility interaction between the two markets. Nazlıoğlu et al. (2013), Xiarchos and Burnett (2018), and Choui-Wei et al. (2019) studied the volatility interaction between the energy market and agricultural products and found evidence for the existence of spillover. Nazlıoğlu et al. (2013) evaluated the data before and after the crisis and stated that there is a spillover from wheat to the oil market for both periods, but that the spillover before the crisis is not effective for other markets. Wang and Guo (2018), Green et al. (2017), and Chen et al. (2019) investigated the volatility spillover between the oil market and the carbon market in their study. Wang and Guo (2018) analyzed the volatility spillover between WTI, Brent, and natural gas using the method developed by Diebold and Yılmaz (2012) and found that there is spillover from the oil market to the carbon market. In their study, Green et al. (2018) examined the spillover effects of the shocks in gas, coal, and carbon emission prices in the German energy market to the electricity market and found that coal and gas has a significant spillover effect for carbon. In their article, Chen et al. (2019) investigated the interaction between EUA emission prices with oil, coal and gas prices using the asymmetric BEKK model, and found that there is a relatively stable and positive correlation between EUA, Brent and natural gas. Chang et al. (2015; 2018) examined the theoretical framework and analyzed the volatility spillover effects using multivariate and univariate models, BEKK and DCC.

Another important issue to be examined in volatility spillover is the interaction between the oil market and stock markets. Chen et al. (2018), Liu et al. (2020), Ping et al. (2018) and Kumar et al. (2019) conducted studies on this subject. Chen et al. (2018) analyzed the relationship between the crude oil market and Chinese new energy stock prices with VAR and multivariate GARCH models and found that there is a unidirectional spillover from the crude oil market to Chinese new energy stock prices. Liu et al. (2020) examined the volatility spillover between the US stock market and the oil market, and concluded that there is a positive correlation between the two markets, the correlation increased during the crisis periods, and there is a bidirectional spillover. Ping et al. (2018) used the DCC-GARCH model in their study examining the relationship between the Chinese oil spot, futures and energy exchanges and stated that there is bidirectional spillover between oil spot and futures as well as oil spot and energy exchange, while unidirectional spillover from the futures market to the energy exchange exists. By using the MGARCH model, Kumar etc. (2019) found that there is a negative market shock spillover among crude oil, natural gas and stock prices in India.

With the development of ARCH and GARCH models by Engle (1982) and Bollerslev (1986), many studies have been conducted to evaluate the volatility in energy commodity prices (Efimova and Serletis, 2014, p.264). Lin and Tamvakis (2001) applied univariate and bivariate ARCH and GARCH models to examine whether there is a price transmission in the crude oil and petroleum products markets, and found that there is interaction in the two markets. Ewing et al. (2002) examined the volatility spillover between oil and natural gas markets with multivariate GARCH models and concluded that there is a spillover between the two markets. Hammoudeh and Li (2003) examined the spillover and causality of crude oil, gasoline and heating oil spot, and futures prices in different locations such as NYMEX, Los Angeles, Gulf Coast and Rotterdam, and concluded that there is bidirectional causality in spot and futures prices of NYMEX gasoline and that spot prices produce the largest spillovers. Lee and Zyreen (2007) examined the volatility spillover between crude oil, gasoline and heating oil and the effects of changes in OPEC's prices, and stated that changes in the crude oil market increase volatility and shocks in the market are short-lived. Chang et al. (2009) used the CCC and VARMA-GARCH models for the volatility spillover between crude oil futures returns and oil company stock returns. According to the VARMA-GARCH and VARMA-AGARCH model, there is no spillover in any return pair, but according to the CCC model, they found a low correlation between WTI and stock returns. Arouri et al. (2011), in their study, examined the volatility spillover between the Gulf Countries (GCC) and oil prices with the VAR-GARCH approach, and stated that there is a significant return and volatility spillover between GCC stock exchanges and oil prices. Sita and Abosedra (2012) used GARCH models for the interaction between crude oil, gasoline, heating oil, and natural gas and concluded that shocks in oil markets are weak in determining shocks in natural gas markets. Wei and Chen (2014) examined whether the volatility of WTI returns is affected by Texas Light Sweet and euro, dollar and S&P 500 energy index returns with the multivariate GARCH model, and determined that WTI is affected by its past volatility, exchange rate returns and energy index returns. Wilmot (2014) examined the volatility spillover between US and Canadian energy commodities with the multivariate GARCH model and stated that there is a spillover from the US to Canada. Efimova and Serletis (2014) measured the volatility spillover in oil, natural gas and electricity prices with univariate and multivariate GARCH models and found that there is spillover from oil to gas and electricity markets. Lin and Li (2015) examined the spillover between the crude oil and natural gas markets of the USA, Europe and Japan within the framework of VEC-MGARCH and stated that the volatility in the oil market bidirectionally spillover to the natural gas market in both the USA and Europe. There is no volatility in the natural gas and oil markets in Japan. Zhang and Sun (2016) used DCC-GARCH and BEKK-GARCH models to carbon futures and fossil fuel (Brent, coal, natural gas) data and concluded that while there is a unidirectional spillover from the coal market to the carbon market, from the carbon market to the natural gas market, there is no spillover between carbon and Brent. In their study, Maraqa and Bein (2020) examined the Stainability Stock Indices (SSIs), international crude oil prices, and the volatility spillover among European importer and exporter countries with the DCC-GARCH model. While there is a high correlation between exporting countries and the oil market, a high correlation is found between oil importing countries and SSIs. Akhtaruzzaman et al. (2020) used the VARMA DCC-GARCH model to investigate the volatility spillover between financial and non-financial institutions in China and the G7 countries in their study conducted during the COVID-19 period and stated that China and Japan are the net transmitters of spillovers in this period, and that financial firms are important in volatility spillovers compared to non-financial firms.

The summary of the literature regarding the volatility spillover is presented in Table 1.

Table 1: Summary of literature review

Authors	Sample	Data set	Model	Result
Lin and Tamvakis(2001)	NYMEX-IPE	January 4, 1994 - June 30, 1997	ARCH-GARCH	There is a volatility spillover.
Ewing et al. (2002)	Crude Oil and Natural Gas	April 1, 1996-October 29, 1999	GARCH-BEKK Model	Spillover between two markets
Hammoudeh et al.(2003)	WTI, Heating oil, Gasoline spot and futures	1986-2001	GARCH Model and Cointegration test	There is causality between gasoline spot and futures and spot prices have the most spillover
Lee and Zyren (2007)	Crude oil, motor gasoline, heating oil	January 1990-May 2005	GARCH / TARCH model	High volatility shocks in the crude oil market are short-lived.
Chang et al.(2009)	WTI company stocks	November 14, 1996-February 20, 2009	CCC Model VARMA-GARCH VARMA-AGARCH	Correlation is low compared to the CCC model No spillover compared to GARCH models.
Arouri et al.(2011)	Oil and stock markets of countries in the GCC region	June 7, 2005-February 2, 2010	Var- GARCH Model	Spillover between oil prices and stock markets

Sita and Abosedra (2012)	WTI, Heating oil, Natural Gas, Petrol	November 1, 1993 - April 20, 2005	TGARCH Model	Shocks in the oil market are weak in detecting shocks in the natural gas market
Wei and Chen (2014)	WTI, S&P 500, US dollars and Euros	January 4, 2000 - September 30, 2009	GARCH-BEKK Model	Interaction, spillover between oil prices and other variables
Wilmot (2014)	WTI, natural gas	2000-2014	VAR-BEKK Model	Interaction between two markets
Efimova and Serletis (2014)	Crude oil, Natural gas and electricity	January 2, 2001-April 26, 2013	Univariate and multivariate GARCH(DCC and Trivariate BEKK)	Unidirectional spillover from oil to natural gas and electricity markets
Lin and Li (2015)	Brent, natural gas	January 1992-December 2012	VEC-MGARCH Model	There is a bidirectional spillover between oil and natural gas in the USA and Europe, There is no spillover between oil and natural gas in Japan.
Zhang and Sun (2016)	Brent, coal, natural gas, Carbon futures	January 2, 2008-September 30, 2014.	DCC-GARCH and BEKK-GARCH	There is a unidirectional spillover from coal to the carbon market and from the carbon market to natural gas, There is no spillover between the carbon market and Brent.
Wang and Guo (2018)	WTI, Brent , Natural Gas	January 10, 2006 - May 31, 2017	Diebold and Yılmaz Method	Spillover from the oil market to the carbon market
Green et al.(2017)	German Energy Market (Coal, Gas, Carbon)	January 3, 2008 - March 31, 2016	VAR-BEKK and Impulse Response Analysis	Significant spillover from carbon low, coal and gas to the electricity market
Chen et al (2019)	Brent , Coal, Natural Gas	April 22, 2005- July 17, 2018	Asymmetric BEKK, Var Model	Volatility spillover between EUA prices and Brent
Chen et al.(2018)	Crude oil, China New Energy Market	January 1, 2010-December 31, 2014	Var and Multivariate GARCH	Unidirectional spillover from crude oil to the Chinese energy market
Liu et al.(2020)	Crude oil, US exchange rate	January 1996- April 2019	TVP-VAR	Positive correlation between two markets, bidirectional spillover
Ping et al.(2018)	China Oil spot-futures market	August 26, 2004 - January 21, 2016	VAR-BEKK-GARCH Model	Oil spot-futures-energy stock bidirectional spillover, Unidirectional spillover from energy exchange to oil futures
Akhtaruzzaman et al.(2020	China and G7 countries financial-non-financial firms	January 1, 2013-December 30, 2019	VARMA-DCC-GARCH Model	China and Japan are net transmitters of spillovers.

Data Set and Methodology of The Study

In the study, in order to determine the return and volatility spillover between the energy market commodities, a total of 3394 data regarding the spot prices of Brent oil (Europe), No.2 Heating Oil (New York Harbor), Natural Gas (Henry Hub), WTI crude oil (Cushing, Oklahoma) between 01.01.2008-31.12.2020 were evaluated. The data of the study were retrieved from “U.S. Energy Information Administration” and “Investing.com”. All data were synchronized and date unity was achieved. In order to get more accurate results from the analysis, daily data were converted into continuous composite logarithmic return series. For this purpose;

the formula r_t = 100 * [ln (P_t) – ln (P_{t-1})] is used. (1)

In the formula, r_t represents the return of the series at t time, P_t shows the closing price of the index at t time, and P_{t-1} …

ARCH Model (Autoregressive Conditional Heteroskedasticity)

The time series follows the same course throughout a certain period, after a certain period of time, the fluctuation increases and returns to its old course. If the long-term variance of these series is constant and the variance is different in the high or extreme fluctuation period, these series are called conditional heteroskedasticity series. The ARCH model developed by Engle (1982) expresses the conditional variance of the error term with the square of the past values of the error term (Çelik and Kahyaoğlu, 2021, p.316).

ARCH process;

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + u_t \qquad u_t \sim N(0, \sigma_t^2) \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \alpha_3 u_{t-3}^2 + \ldots \alpha_p u_{t-p}^2 \tag{3}$$

α in Equation 3 represents unknown ARCH parameter while p represents the number of delays. If the conditional variance of $u_t$is explained by the square of the error of u_t one period ago, the ARCH (1) process is explained by equation 4 (Çelik and Kahyaoğlu, 2021, p.317).

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{4}$$

GARCH Model (Generalized Autoregressive Conditional Heteroskedasticity)

The basic assumption of traditional time series and econometric models is that they have a constant variance. The ARCH (Autoregressive Conditional Heteroskedasticity) process of Engle (1982) makes it possible for the conditional variance to change over time as a function where the errors leave the constant unconditional variance. Empirical implementations of the ARCH model provide a long delay in the conditional variance equation, and a fixed lag structure is typically specified to avoid problems with negative variance parameter estimates. ARCH models allow both longer memory and more flexible delay structure (Bollerslev 1986, p.308).

Engle's work was developed by Bollerslev (1986). Error process;

As $\hat{u}_t = v_t \sqrt{h_t}$ $\sigma_v^2 = 1$, h_t value (5)

$$h_t = \beta_0 + \sum_{k=1}^{q} \beta_k u_{t-k}^2 + \sum_{k=1}^{p} \Upsilon_k \, h_{t-k} \tag{6}$$

v_t (White-noise process) (Kutlar,2017:84).

EGARCH Model (Exponential Generalized Autoregressive Conditional Heteroskedasticity)

The exponential GARCH model is an asymmetric model proposed by Nelson (1991). Therefore, positive and negative shocks are assumed to have different effects on volatility (Çelik and Kahyaoğlu, 2021, p.340). There are many ways to get the conditional variance. It can be modeled as follows;

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\left|\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| - \sqrt{\frac{2}{\pi}} \right] \quad (7)$$

It has many advantages over the model's GARCH specification. Since log (σ_t^2) is modeled in the first place, σ_t^2 will be positive even if the parameters are negative. Thus, there is no need to apply constraints to the model parameters in a restricted manner. Second, the EGARCH formulation allows for asymmetries, if the relationship between volatility and reversal is negative, then γ will be negative. Nelson (1991) used the Generalized Error Distribution for errors in his original formulation. GED is a large family of distributions that can be used in many series. Moreover, with its computational ease and intuitive interpretation, almost many implementations of EGARCH use conditional errors rather than GED (Brooks, 2008, p.406).

VAR-EGARCH Model

The EGARCH model introduced by Nelson (1991) was developed by Koutmos and Booth (1995) as a multivariate EGARCH model. Koutmos (1996) extended this model and proposed the multivariate VAR-EGARCH model to measure the spillovers in both return and volatility. (Dear et al,2020, p.451). The multivariate VAR-EGARCH model is as follows (Koutmos, 1996: 977):

$$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{n} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t}, \quad (8)$$

$R_{i,t}$: percent return of market i at time t

$\sigma_{i,t}^2$: Conditional variance

Equation is a function of the conditional mean of each asset, its past returns, as well as past returns among assets. It represents a vector autoregression (VAR) returns for each asset. Predecessor/Successor relations take place with the coefficients $\beta_{i,j}$ for $i \neq j$. The $\beta_{i,j}$ coefficient will actually be used to estimate the existence of i as the cause of the existence of j or the returns of the entity j in the presence of i in the future.

$$\sigma_{i,t}^2 = \exp \{\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,jfj} (z_{j,t-1}), + \gamma_i \ln(\sigma_{i,t-1}^2)\}, \quad (9)$$

The conditional variance of current returns on each asset in the equation is an exponential function of standardized innovations between itself and assets in the past period. This indicates γ_i volatility persistence. Special functional form of $f_j\ (z_{j,t-1})$;

$$f_j\ (z_{j,t-1}) = (|z_{j,t-1})| - \mathrm{E}\ |(z_{j,t-1})| + (\delta_j\ z_{j,t-1}), \quad (10)$$

$$\sigma_{i,j,t} = \rho_{i,j}\ \sigma_{i,t}\ \sigma_{j,t} \quad , \text{i,j} = 1,2,3,\ldots, \text{N ve } i \neq j \quad (11)$$

According to the equation $(|z_{j,t-1})|$- E $|(z_{j,t-1})|$ tests the size effect, and $(\delta_j\ z_{j,t-1})$ tests the leverage effect. $f\ (\cdot)$ is an asymmetric function of standardized innovations in the past. The slope of $f\ (\cdot)$ is 1 + δ_j if $z_{j,t-1} < 0$, while it is 1+ δ_j if $z_{j,t-1} > 0$.

Volatility interactions or fluctuations between markets are measured by $\alpha_{i,j}$ for i, j = 1, 2, 3, 4 and $i \neq j$. When the positive is combined with the negative, this indicates that the negative innovations in the presence of j have a greater effect on the volatility of the asset i than the positive innovations. This specification indicates that the return correlation of assets i and j is fixed or synonymous. The covariance is proportional to the product of the standard deviations. The VAR-EGARCH model is formulated as follows;

$$\mathrm{L}(\Theta) = -0{,}5\ (NT) \ln(2\pi) - 0{,}5 \sum_{t=1}^{T} (\ln |S_t| + \epsilon' S_t^{-1} \epsilon_t) \quad (12)$$

In the equation, N represents the number of equations, T is the number of observations, Θ 54x1 is the parameter vector to be estimated, $\epsilon' = [\epsilon_{1,t}, \epsilon_{2,t}, \epsilon_{3,t}, \epsilon_{4,t}]$ shows the vector of innovations occurring in time t, and 1x4, S_t represents the conditional variance-covariance matrix that changes according to 4x4 time (Koutmoss, 1996, p.978).

Findings

The information regarding the energy commodities whose data were analyzed within the scope of this study is as follows. Brent is located in the North Sea in the north east of England. It is a type of crude oil that takes its name from the first letters of the names of five different layers (Broom, Rannoch, Etieve, Ness, Tarbat) from which it is obtained. Brent is still considered as the reference price for oil of Middle Eastern and African origin in the European market. Brent type oil accounts for almost 2/3 of crude oil transactions worldwide and is also traded on ICE and NYMEX exchanges.

Heating Oil is a petroleum product refined from crude oil. It is primarily used as a distilled fuel sold for use in boilers, furnaces, and water heaters. Some commercial and institutional buildings use heating oil in direct water heating equipment and in combined heat and power plants. The United States has two sources of heating oil: domestic oil refineries and imported from different countries. Existing refineries meet the majority of consumption. Heating oil imports are mostly procured during the winter months to help meet consumer demand in the Northeast. Distillates are transported across the USA by pipelines, tankers (ships), barges, trains and trucks (EIA, 2019, p.1).

Natural Gas consists of a mixture of gaseous hydrocarbons deposited in reservoirs of porous rock (usually sand or sandstone) covered with impermeable layers. It is often associated with petroleum, with which it has a common origin in decomposition of organic matter in sedimentary deposits. It is used as industrial and domestic fuel, to make carbon black and chemical synthesis. Natural gas is transported by large pipelines or (as liquid) refrigerated tankers (EIA, 2019, p.1). Henry Hub is the natural gas pipeline located in Erath, Louisiana, which is the legal place of delivery for futures on the New York Mercantile Exchange (NYMEX). The center is owned by Sabine Pipe Line LLC and has access to most of the major gas markets in the United States. The hub connects to four intra-country and nine interstate pipelines, which include the Transcontinental, Acadian, and Sabine pipeline. The NYMEX contract at Henry Hub began in 1990 and the prices established at Henry Hub are used as benchmarks for the North American natural gas market and a portion of the global liquid natural gas (LNG) market. In other natural gas markets, such as Europe, hub pricing points are fragmented, which means that natural gas prices are generally indexed for crude oil (Chen, 2019, p.1).

WTI stands for West Texas Intermediate. Located in the main oil region of the United States, this crude oil is light, sweet, high quality and has a low sulfur content. Refinement and transportation operations affect the quality, cost, and prices of crude oil. Both crude oil and refined products are traded on the New York Mercantile Exchange (NYMEX) through futures contracts (Azevedo et al.,2015, p.396).

The charts of the price series of energy commodities are shown in figure 1 and the charts of the logarithmic return series is shown in figure 2.

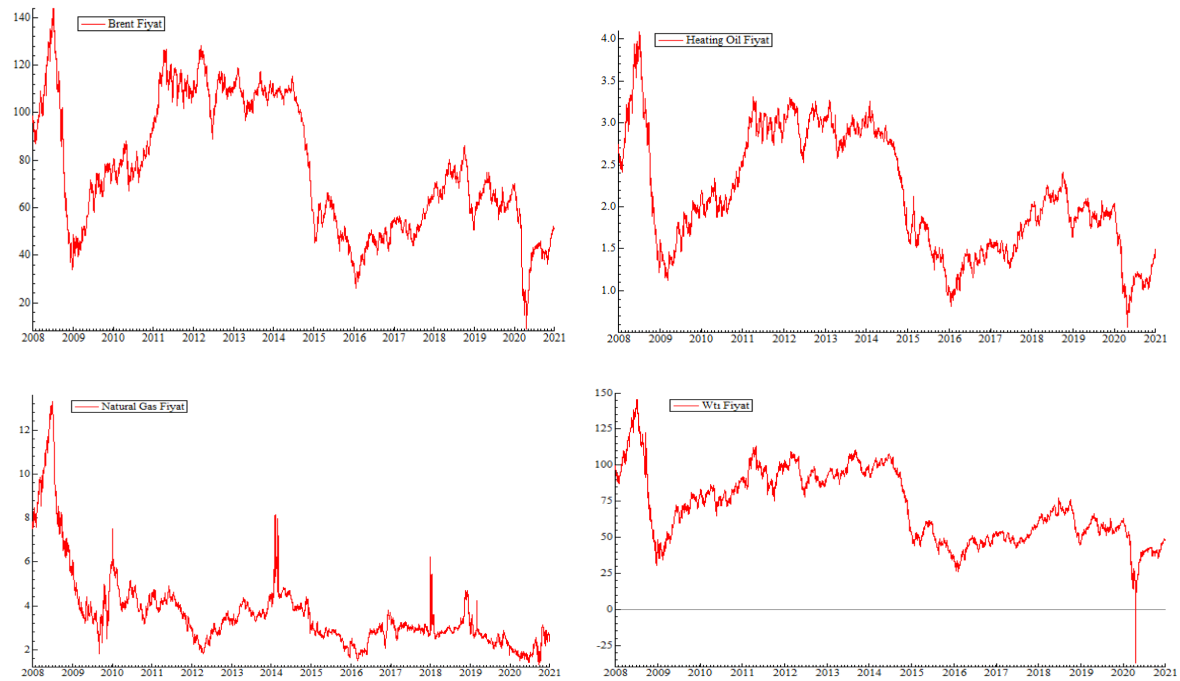


Figure 1: Price Series Charts of Energy Commodities

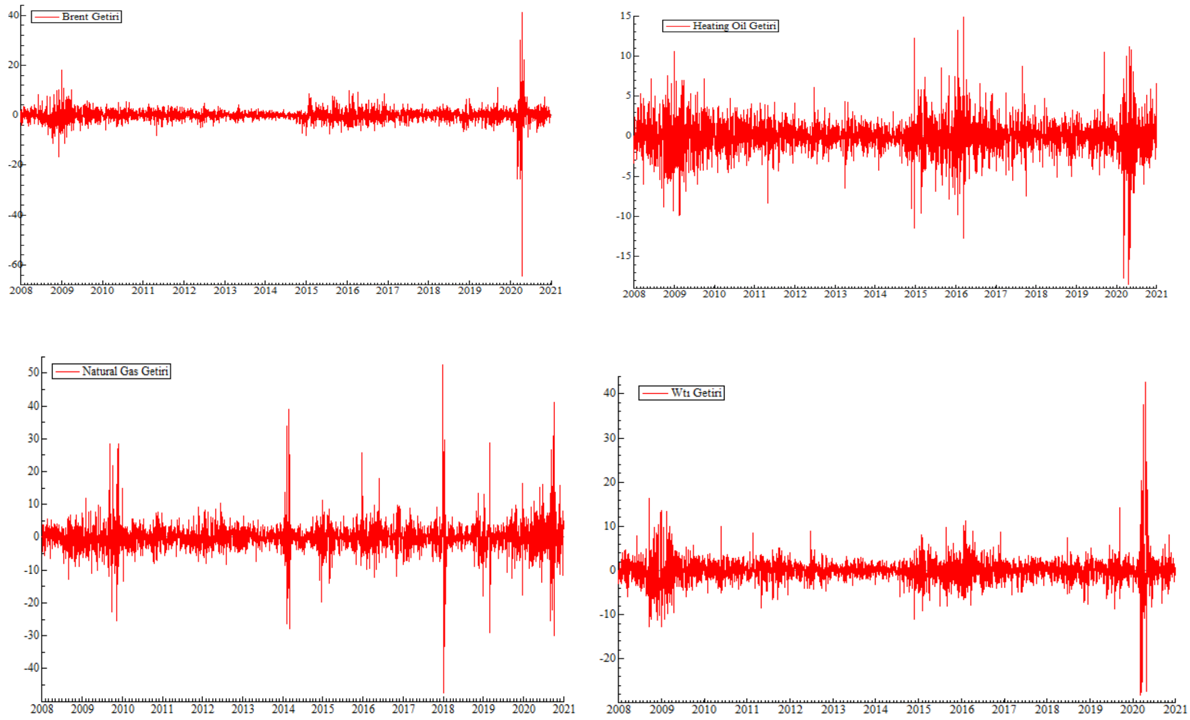


Figure 2: Logarithmic Return Charts of the Return Series of Energy Commodities

When Figure 1, which expresses the price charts of energy commodities, is examined, it is seen that there are many up and down price movements. In this case, it is concluded that energy commodities are sensitive to market factors. There are volatility clusters in the return charts shown in Figure 2. The effect of COVID-19 on energy commodities is clearly seen in both price and return charts. In particular, WTI prices have been the most affected commodity during the COVID-19 period. With the WHO's declaration of COVID-19 as a pandemic in

March, oil demand was most affected by the restrictions. At the end of April, the price of oil per barrel decreased to $18. In May, inventory costs exceeded oil prices (contract prices) due to excess stocks in Cushing warehouse and distribution regions in Oklahoma, which is of great importance for WTI, and refineries giving up oil purchases at the end of the maturity period. The contract holders wanted to transfer their WTI contracts, but the contract prices turned negative because they were too high (Dikkaya and Rzali, 2020, p.407-408).

The descriptive statistics of the energy commodities included in the study are given in Table 2.

Table 2: Descriptive statistics of logarithmic return series

	Brent	Heating oil	Natural Gas	WTI
Mean	-0.018898	-0.018048	-0.031718	-0.00013216
Median	0.000000	0.000000	0.000000	0.000000
Maximum	41.202	14.862	52.535	42.583
Minimum	-64.37	-18.46	-47.561	-28.138
Std. Deviation	2.846	2.2347	4.4541	2.9672
Skewness	-2.6257	-0.32416	0.76459	0.14619
Kurtosis	101.94	7.4190	23.868	24.959
Jargue-Bera	1472700.0	7838.7	80844.	83281.
Numbers of Observation	3394	3394	3394	3394

When the descriptive statistics of energy commodities are examined in Table 2, it is seen that the standard deviation of the heating oil data is close to other petroleum products, but it has the lowest value among the four commodities. The skewness of Brent and heating oil data is negative, that is, it shows a left-skewed distribution. Natural gas and WTI data are positive and skewed to the right. The kurtosis values are quite high and all four energy commodities show a sharp distribution. The high Jarque-Bera values indicate that the data do not indicate a normal distribution.

One of the frequently encountered problems in time series is stationarity. Problems are encountered when interpreting analyzes without stationarity. When applying nonlinear methods, the problem becomes more complicated because it is necessary to examine the time-dependent variation of the nonlinear properties of the series (Manuca and Savit, 1996, p. 134).

Table 3: Unit Root Test Results

	Return Series		
	ADF	**PP**	**KPSS**
Brent	-34.44620**	-58.89516**	0.036291
Heating oil	-33.4943**	-60.01761**	0.054594
Natural gas	-39.3715**	-63.61043**	0.060088
WTI	-35.3977**	-61.9996**	0.077447

** Indicates 5% significance level.

ADF (Augmented Dickey Fuller), PP (Phillips-Perron) and KPSS (Kwiatkowski, Phillips, Schmidt and Shin) unit root tests are given in order to determine the stationarity of the series in Table 3. While ADF and PP tests state the "null hypothesis" unit root, non-stationarity or I[1], the KPSS test shows the I[0] process, which means stationarity. According to the ADF and PP tests applied to Brent, heating oil, natural gas and WTI returns, it is seen that the null hypothesis of unit root is rejected, while the I[0] process is reached for the result of the KPSS test statistics, and the null hypothesis cannot be rejected. As a result, there is no unit root in the series and it is seen that the series are stationary.

Perron (1989) showed that the rejection ability of the null hypothesis of unit root decreases when the alternative of the null hypothesis of unit root is true and the existing structural break is not taken into account. In their study, Lee and Strazicich (2003, 2004) made an evaluation in which the break date is determined internally, allowing one to two breaks under the null hypothesis of unit root and its alternative. The test presented by Lee-Strazcich is based on the lagrange multipliers (LM) unit root test presented by Schimidt and Phillips (1992).

Lee and Strazicich (2003) stated in their study that ignoring an existing break will cause the test to lose power. In addition, they also stated that power loss would occur in case of two or more breaks in tests with a single break. The results of the Lee-Strazicch test are given in the table with the critical values of 1%, 5% and 10%. T statistic values were compared by examining the critical table values given by LS (2003). If the t statistic calculated in the analysis is greater than the absolute value of the critical table values, the hypothesis that the series is stationary with the determined break dates is accepted. In other words, the null hypothesis of "the existence of a unit root in the series without structural break" is rejected. The rejection of the null hypothesis as a result of the two-break unit root test means trend stationarity (İğde, 2010, p.68).

Table 4: Lee-Strazich Unit Root Test

Energy Commodities	k	T. Statistics	13.04.2011		17.02.2016	
			D_{1t}	DT_{1t}	D_{2t}	DT_{2t}
Brent	3	(-26.8584)	**(2.3407)**	(-20.0830) *	(-5.0046) **	**(24.9630)**
%1 Critical Value	-5.2120					
%5 Critical Value	-4.7340					
%10 Critical Value	-4.5340					

Heating Oil	k	T.Statistics	21.05.2009		21.11.2016	
			D_{1t}	DT_{1t}	D_{2t}	DT_{2t}
	3	(-28.6834)	(-4.6959) ***	**(25.3681)**	**(2.2926)**	(-26.0924) *
%1 Critical Value	-5.0990					
%5 Critical Value	-4.7160					
%10 Critical Value	-4.4810					

Natural Gas	k	T.Statistics	14.10.2009		10.01.2018	
			D_{1t}	DT_{1t}	D_{2t}	DT_{2t}
	3	(-30.9744)	(-12.2865) *	**(30.0605)**	**(5.9880)**	(-30.3629) *
%1 Critical Value	-5.2470					
%5 Critical Value	-4.7760					
%10 Critical Value	-4.4720					

WTI	K	T.Statistics	21.11.2017		27.06.2019	
			D_{1t}	DT_{1t}	D_{2t}	DT_{2t}
	5	(-11.9561)	(-0.6096)	(2.7092)	(3.7523)	(-11.2466) *
%1 Critical Value	-5.1160					
%5 Critical Value	-4.5390					
%10 Critical Value	-4.1950					

The break times of energy commodities are given in the table. k is the optimal delay number, the values in parentheses belong to the t statistic, and the bold ones are the statistical values for which the break times are meaningless.
* indicates %1; ** indicates 5% and *** indicates 10% significance levels.

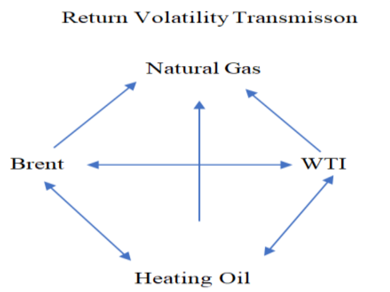
According to the results of the test with two breaks at the level and skewness applied to the Brent return series, the test statistic value is greater than the critical values of the Lee-

Strazicich (2003) test in absolute value. As a result, the basic hypothesis of the structural break unit root of the return series is rejected. That is, the return series are stationary. It is seen that two breaks at the level and skewness of the Brent return series are significant. In addition, the first break date in the series is 13.04.2011 while the second break date is 17.02.2016. It is seen that the test statistic value obtained according to the two-break unit root test results at the level and skewness of the heating oil return series is greater than the critical values specified in the Lee-Strazicich (2003) test in absolute value. It has been determined that two breaks at the level and skewness of the heating oil return series are significant and the first break date is 21.05.2009 while the second break date is 21.11.2016. In the natural gas return series, on the other hand, the test statistic value is greater than the critical values of the Lee-Strazicich (2003) test in absolute value, according to the results of the two-break test at level and skewness. The series is stationary. The first break date is 14.10.2009, the second break is on 10.01.2018. It is seen that the WTI return series is also stationary. The first break date is 21.11.2017 and the second break date is 27.06.2019.

Table 5: Multivariate VAR (4)-EGARCH (1,1) Model Conditional Mean Results

Conditional Mean Equation

$R_{i,t} = \beta_{i,0} + \sum_{j=1}^{N} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t}$, *for i,j = 1,2,3,4.*



Brent				$\beta_{1,1}R_{1,t-3}$	$\beta_{1,1}R_{1,t-4}$	$\beta_{1,2}R_{2,t-1}$	$\beta_{1,2}R_{2,t-2}$	$\beta_{1,2}R_{2,t-3}$	$\beta_{1,2}R_{2,t-4}$
				0.0002 (0.0172)	-0.0384 (-3.7006) **	0.2963 (22.4037) **	0.1071 (6.7670) **	0.0115 (0.7723)	0.0040 (0.3568)
				$\beta_{1,3}R_{3,t-3}$	$\beta_{1,3}R_{3,t-4}$	$\beta_{1,4}R_{4,t-1}$	$\beta_{1,4}R_{4,t-2}$	$\beta_{1,4}R_{4,t-3}$	$\beta_{1,4}R_{4,t-4}$
				0.0018 (0.5020)	-0.0022 (-0.3621)	0.0169 (1.5195)	-0.0043 (-0.3652)	0.0355 (3.8163) **	0.5178 (40.9296) **
WTI				$\beta_{2,1}R_{1,t-3}$	$\beta_{2,1}R_{1,t-4}$	$\beta_{2,2}R_{2,t-1}$	$\beta_{2,2}R_{2,t-2}$	$\beta_{2,2}R_{2,t-3}$	$\beta_{2,2}R_{2,t-4}$
	[illegible] (0.9166)	[illegible] (11.0461) **	[illegible] (6.0064) **	0.04581 (4.9955) **	-0.0256 (-1.9712) **	-0.1143 (-13.9467) **	-0.0888 (-8.6339) **	-0.0500 (-8.2047) **	-0.0221 (-1.9166)
		$\beta_{2,3}R_{3,t-1}$	$\beta_{2,3}R_{3,t-2}$	$\beta_{2,3}R_{3,t-3}$	$\beta_{2,3}R_{3,t-4}$	$\beta_{2,4}R_{4,t-1}$	$\beta_{2,4}R_{4,t-2}$	$\beta_{2,4}R_{4,t-3}$	$\beta_{2,4}R_{4,t-4}$
		-0.0059 (-1.5591)	-0.0015 (-0.4193)	0.0035 (0.8183)	-0.0059 (-1.4080)	0.0127 (1.5918)	0.0060 (0.6841)	0.0134 (2.0961) **	0.6812 (99.0359) **
Natural Gas	$\beta_{3,0}$	$\beta_{3,1}R_{1,t-1}$	$\beta_{3,1}R_{1,t-2}$	$\beta_{3,1}R_{1,t-3}$	$\beta_{3,1}R_{1,t-4}$	$\beta_{3,2}R_{2,t-1}$	$\beta_{3,2}R_{2,t-2}$	$\beta_{3,2}R_{2,t-3}$	$\beta_{3,2}R_{2,t-4}$
	-0.0385 (-1.1726)	-0.0596 (-3.2245) **	0.01377 (1.1632)	0.0553 (3.0753) **	-0.0642 (-6.0545) **	0.1328 (14.5520) **	0.01297 (2.5699) **	0.0090 (0.9657)	0.0693 (10.6727) **
		$\beta_{3,3}R_{3,t-1}$	$\beta_{3,3}R_{3,t-2}$	$\beta_{3,3}R_{3,t-3}$	$\beta_{3,3}R_{3,t-4}$	$\beta_{3,4}R_{4,t-1}$	$\beta_{3,4}R_{4,t-2}$	$\beta_{34}R_{4,t-3}$	$\beta_{3,4}R_{4,t-4}$
		0.0275 (2.2514) **	-0.1040 (-7.3839) **	-0.0545 (-6.8172) **	-0.0126 (-1.8083)	-0.0072 (-0.3538)	-0.0040 (-0.2353)	0.0749 (3.5224) **	0.0114 (0.9431)
Heating oil	$\beta_{4,0}$	$\beta_{4,1}R_{1,t-1}$	$\beta_{4,1}R_{1,t-2}$	$\beta_{4,1}R_{1,t-3}$	$\beta_{4,1}R_{1,t-4}$	$\beta_{4,2}R_{2,t-1}$	$\beta_{4,2}R_{2,t-2}$	$\beta_{4,2}R_{2,t-3}$	$\beta_{4,2}R_{2,t-4}$
	-0.0164 (-0.5972)	0.0652 (34.7995) **	0.04398 (3.0923) **	0.0032 (0.3381)	0.0409 (4.8391) **	-0.0448 (-12.9675) **	-0.0214 (-3.1151) **	0.0119 (1.5287)	-0.0191 (-2.2145) **
		$\beta_{4,3}R_{3,t-1}$	$\beta_{4,3}R_{3,t-2}$	$\beta_{4,3}R_{3,t-3}$	$\beta_{4,3}R_{3,t-4}$	$\beta_{4,4}R_{4,t-1}$	$\beta_{4,4}R_{4,t-2}$	$\beta_{4,4}R_{4,t-3}$	$\beta_{4,4}R_{4,t-4}$
		0.0066 (1.0788)	0.0025 (0.4928)	0.0080 (1.5637)	-0.0079 (-1.6408)	-0.0154 (-1.5712)	-0.0217 (-2.3795) **	-0.0090 (-0.9675)	0.0107 (2.4968) **

() t statistics, $\beta_{1,0}$; Constant Term, $\beta_{i,j}$; Return spillover from product j to product i , $R_{i,t;}$ current period return of product i, $R_{j,t-1}$, $R_{j,t-2}$, $R_{j,t-3}$, $R_{j,t-4}$ = 1,2,3,4 days delayed values of product j,** %5 significance level

Figure 3: Return Volatility Transmisson

In Table 5, the multivariate VAR-EGARCH model is tried to be estimated in the mean and variance to determine the return and volatility spillover of energy commodities. Energy commodities are regressed with their lagged values and it is determined that the lag length between the series for the selection of the most suitable model is determined as the 4th lag with the most appropriate value according to the Ljung-Box test. This model examines the joint modeling of movements in two or more markets and whether return innovations in the market are indicators of the first or second conditional volatility in the other market (Kuttu, 2014,p.5). The vector autoregressive part (VAR) of the VAR (4)-EGARCH (1,1) model defines that the conditional mean in each market is a function of past self-returns as well as cross-market past returns, while the EGARCH is defined as the conditional variance of returns in each market, an exponential function of the past self, the cross market's standardized innovations, and the past self's conditional variance (Koutmos, 1996,p.978). When the results of Table 5 are examined, it is seen that there are multiple and asymmetrical spillover when the return spillover among energy commodities is examined. In this case, it is concluded that the oil market and the natural gas market are affected by each other. Brent and WTI commodities show a correlation with the past returns of other commodities. It is determined that there is a bidirectional spillover among Brent returns with WTI and heating oil, but unidirectional spillover with natural gas and this spillover is from brent to natural gas. There is a bidirectional spillover among WTI returns with heating oil and Brent, but unidirectional spillover with natural gas. The most striking result is that while there is a spillover from oil market products to natural gas returns, there is no spillover from natural gas returns to other petroleum commodities. In other words, it is concluded that natural gas is affected by other energy commodities, but it does not affect other energy commodities. In a similar study, Villar and Joutz (2006) examined the price relationship between WTI and Henry Hub (natural gas) and concluded that crude oil prices are affected by natural gas prices, but natural gas prices do not affect crude oil prices. They explained this situation by determining oil prices on a global scale and natural gas prices on a smaller scale. It is noteworthy that the results obtained are close to the study of Villar and Joutz (2006).

Table 6: Multivariate Var (4) Egarch (1,1) Conditional Variance Results

CONDITIONAL VARIANCE EQUATION

$$\sigma^2_{i,t} = exp\,\{\alpha_{i,0} + \sum_{j=1}^{4} \alpha_{i,j}\, f_j\, (z_{j,t-1}) + \gamma_i\, (\sigma^2_{i,t-1})\},\ for\ i,j = 1,2,3,4.$$

$$\sigma_{i,j,t} = \rho_i \sigma_{i,t}\, \sigma_{j,t},\ for\ i,j = 1,2,3,4\quad i \neq j$$

Brent	Coefficient (T) Statistics	WTI	Coefficient (T) Statistics	Natural gas	Coefficient (T) Statistics	Heating oil	Coefficient (T) Statistics
$\alpha_{(1,0)}$	-0.1728 (-8.1521) **	$\alpha_{(2,0)}$	-0.2137 (-5.5505) **	$\alpha_{(3,0)}$	-0.2230 (-8.6857) **	$\alpha_{(4,0)}$	-0.0975 (-8.2610) **
$\alpha_{(1,1)}$	0.0637 (6.9578) **	$\alpha_{(2,1)}$	0.0628 (1.8540)	$\alpha_{(3,1)}$	0.0722 (7.3496) **	$\alpha_{(4,1)}$	0.0291 (2.8564) **
$\alpha_{(1,2)}$	0.1209 (3.7163) **	$\alpha_{(2,2)}$	0.1969 (2.6698) **	$\alpha_{(3,2)}$	-0.0004 (-0.0237)	$\alpha_{(4,2)}$	0.0422 (3.2115) **
$\alpha_{(1,3)}$	-0.0260 (-2.9879) **	$\alpha_{(2,3)}$	-0.0510 (-4.6105) **	$\alpha_{(3,3)}$	0.3024 (8.2163) **	$\alpha_{(4,3)}$	-0.0225 (-2.8353) **
$\alpha_{(1,4)}$	0.0848 (6.3420) **	$\alpha_{(2,4)}$	0.0940 (9.1422) **	$\alpha_{(3,4)}$	0.0273 (1.9092)	$\alpha_{(4,4)}$	0.0934 (9.0473) **
δ_1	-0.6389 (-5.9702) **	δ_2	-0.0840 (-4.1606) **	δ_3	-0.0265 (-0.6693)	δ_4	-0.3405 (-4.7838) **
γ_1	0.9894 (138.3424) **	γ_2	0.9870 (99.2963) **	γ_3	0.9717 (129.0136) **	γ_4	0.9921 (222.3041) **

$\alpha_{(i,j)}$ = i = j, dependence of product volatility i on its lagged shocks, i ≠ j, dependency of product i volatility on lagged shocks of product j, δ_1 = i, degree of asymmetry of product i (leverage effect), γ_1 = volatility persistence of product i, () t statistics, ** %5 significance level

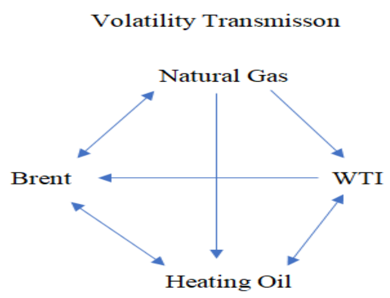


Figure 4: Volatility Transmisson

When the conditional variance equation analysis results of the VAR (4) and EGARCH (1,1) model in Table 6 are examined, it is seen that the volatility spillover exhibits similar results to the return spillover. It can be understood from the statistically significant $\alpha_{(i,j)}$) coefficients that the information shocks between energy commodities spillover and affect each other. As for the volatility spillover, it is seen that there is a multidirectional spillover from Brent oil to heating oil and natural gas, while a unidirectional spillover exists from Brent oil to WTI. Additionally, there is a unidirectional spillover from natural gas to heating oil and WTI. Also, Brent oil, WTI, natural gas and heating oil data are positively affected by their own lagged values and this situation has an increasing effect on volatility. Considering the values indicating the direction of the volatility spillover, it can be said that positive values increase volatility (uncertainty) while negative values decrease volatility.

Values expressed with γ_1 represent the GARCH term. This term expresses that the shock in the markets is permanent for a long time, and this value is close to 1 in all energy products. According to the results of the table, it is seen that the values expressing the permanence of the shock in the market are very close to each other. In other words, energy commodities exhibit equivalent characteristics in terms of the permanence of the shock in the market. However, it is seen that heating oil has the highest value among commodities.

δ_1 refers to the Leverage parameter. Considering the results of Table 6, it is concluded that the values of energy commodities are statistically significant. Additionally, the negative value of the data indicates that bad information in the market has more volatility than good information. It can be stated that heating oil and Brent have the highest leverage effect among energy commodities. That is, negative information about two energy products causes more volatility in the market.

As a result of the tests performed within the analysis, it is seen that there is a problem of changing variance and autocorrelation. The Newey-West estimator was used to calculate the adjusted coefficients obtained from the model.

Table 7: Covariance Matrix between Energy Commodities

	Brent	**WTI**	**Natural gas**	**Heating oil**
Brent	1			
WTI	0.5064	1		
Natural gas	0.0750	0.0432	1	
Heating oil	0.1207	0.1246	-0.0001	1

The modern portfolio theory assumes that both investors and consumers in financial markets include cross-border assets in their portfolios in order to maintain a certain expected return level and to minimize the risks. Considering the assumption that the economic factors are rational and the markets are efficient, it states that choosing the right combination of assets may actually carry a lower overall risk than the current assets in the portfolio. In order to manage risk, financial market users should be familiar with the origins and influencing factors of market volatility and cross-market correlations (Balli et al.2013, p.34). The liberalization and deregulation seen in the financial markets of both developing and developed countries in recent years has ensured the integration of global markets. The possibility that financial assets in national stock markets will be affected by the arising factors may increase risks and decrease profitability. The high correlation between national markets and financial assets means a tendency to act together, which carries many risk factors. Cross-border portfolio diversification contributes to the distribution of risk with different markets and financial assets. The loss that may arise for any reason in different country markets and different financial assets is balanced by making a profit in the other market. The existence of large correlations between markets causes a decrease in the benefits obtained from cross-border portfolio diversification (Gilmore and Mcmanus, 2002, p. 69-70). When the results of Table 7 are analyzed, in terms of cross-border portfolio diversification, the risks of energy commodities are considered low. The low correlation among energy commodities means that the tendency to act together is low, that is, they will not be affected to the same degree by the factors that may occur in the markets. Low correlation is a favorable situation for cross-border portfolio diversification. It is seen that natural gas data among energy commodities has lower values than others. In this sense, natural gas is considered to be suitable for use in the portfolio with different commodities.

Conclusion

Volatility is defined as the variance of return rate. The sensitivity of energy markets is the most important factor affecting volatility. When the literature is examined, it is seen that energy markets are affected by financial crises, macroeconomic indicators, factors seen in different markets, decisions taken by OPEC member countries, and especially supply and demand. In addition, COVID-19, affecting the majority of the world's countries, has had profound effects especially in the energy markets. It will be possible to understand the full effects of the pandemic in the future.

Financial markets and assets interact. In this case, markets and financial assets are affected by common factors, causing a high correlation between them. For market users and investors, it is a risky situation that markets and financial assets have a high correlation. Because these assets tend to act together and exhibit similar behaviors in terms of being affected by risk factors. Price changes and shocks in financial markets affect each other by being transmitted either multidirectionally or unidirectionally. This concept, called volatility spillover, has been extensively studied from different point of views and with different methods. It is named with the concepts of “spillover”, transmission”, “contagion” in the studies. The interaction of energy commodities with different variables and their spillover have been the subjects of many studies in the literature. It is concluded that volatility spillover exists in the vast majority of studies. This means that commodities in the energy market are interacting, and information and shocks are transmitted through the volatility spillover. In this study, return and volatility spillovers among energy commodities are examined with the VAR-EGARCH model. The data covers the dates between 01.01.2008-31.12.2020. It is important that the scope of the study includes the period of COVID-19. Within the scope of the study, the price and return charts of energy commodities are examined and the volatility of the commodities is found to be high. Descriptive statistics of the data are arranged and it is concluded that energy commodities do not provide a normal distribution. The stationarity of the series is examined with unit root tests and it is seen that the series are stationary as a result of ADF, PP and KPSS tests. The VAR (4)-EGARCH (1,1) model is applied to the return and volatility series of energy commodities. When the results of the return series are examined, it is concluded that the other commodities other than the natural gas return series affect each other multidirectionally, but the natural gas returns are affected by the oil returns, but it does not affect the oil returns. Although the oil market and natural gas market are thought to be substitutes and equivalents, it can be said that there is a difference in sensitivity to the market. In addition, if the COVID-19 period is considered, the supply-demand imbalances seen in the oil market and natural gas market are reflected in the prices. Restrictions around the world have affected commercial activities and many institutional and organizational activities have come to a standstill. In addition to the use of natural gas in commercial activities together with petroleum products, its use in heating should also be considered. In the study, it is found that while the natural gas return series is affected by the oil series, the return spillover due to itself do not affect the other series. As Villar and Joutz (2006) states in their study, this can be explained by determining the prices of the oil market on a global scale and the natural gas market on a regional scale. In addition, the shale gas studies carried out by the USA since the 90s are thought to affect the natural gas market.

When the spillover effects in volatility are examined, it is seen that results similar to the return series are obtained. While the heating oil series spillovers multidirectionally with Brent and WTI, it spillovers unidirectionally with the natural gas series. It is seen that the only energy commodity in which natural gas spillovers bidirectionally is Brent. It is seen that energy commodities affect each other in both return and volatility series, and information and shocks are transmitted. In addition, it has been concluded that shocks are permanent for a long time and bad information increases the volatility in the market more than good information according to the leverage parameter. According to the articles examined in the literature section, it is seen that other studies, except for Chang et al. (2009), give similar results with this study in terms of spillover presence among energy commodities. In their studies, Lin and Tamvakis (2001), Ewing et al. (2002), Wei and Chen (2014), Wilmot (2014), Ping et al. (2018) and Liu (2020) concluded that there is a multidirectional spillover among commodities and markets, and reached similar results in terms of multidirectional spillover among oil commodities in return and volatility. In terms of returns, the natural gas market has a different spillover from oil commodities. Sita and Abosedra (2002), Lin and Li (2015) obtained different results in terms of natural gas market spillover, and their studies also overlaps in terms of the natural gas market not affecting energy commodities in return spillover. Zhang and Sun (2016) stated in their study that there is a unidirectional spillover to natural gas, and it is seen that the return and volatility are similar to the unidirectional effect of natural gas data from energy commodities.

In future studies, volatility spillover may be tested among different energy commodities and by changing the date scopes to fully see the effects of COVID-19. In addition, the COVID-19 period may be evaluated in terms of the resulting effects by examining the historical data that deeply affect the energy market.

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