Oil and Stock Markets in Ongoing Flux: Impact of Current Events on Oil Price and Stock Market Performance

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Abstract. *The price of oil and, indirectly, the performance of stock indices have been significantly affected by the events of recent years, with a negative impact on the global economy, including the evolution of the energy market in the context of the transition to renewable energy sources and changes in global energy policy. This paper proposes a comprehensive analysis of the evolution of stock indices, oil market volatility and investors' response to the "black swan" events that have recently caused changes in the global economy. Using advanced econometric and statistical models, the paper presents the complex relationship between the analyzed stock indices, the trends and changes that occurred within them and the relevant influencing factors, such as the price of Brent Oil and the Baltic Dry Index. The results obtained, based on univariate GARCH models (GJR-GARCH) and multivariate DCC-GARCH models are in accordance with specialized studies in the field and show that oil price fluctuations were higher at the beginning of the Covid-19 pandemic compared to the period after the military conflicts (stage in which no significant influence of the oil price on the stock market is observed). Also, using the Chow test, in the analyzed period there are 3 important breaking points that coincide with the dates when the COVID-19 pandemic began, the military conflict between Russia and Ukraine as well as the military conflict between Israel and Gaza, events with a strong impact on the economy. The obtained results also show another important aspect, namely that, during the selected period January 2019-November 2023, the price of oil and the stock market were much more affected by the COVID-19 pandemic than by military conflicts, which cannot be also stated in the case of the price of the Baltic-Dry Index.*

Keywords: correlation, “black swan” events, GJR-GARCH model, oil price fluctuation, DCC-GARCH model.

Introduction

In the current economic context, the stock and oil markets are interconnected and are significantly influenced by a multitude of factors including global medical conditions, geopolitical tensions between states, conflicts in key oil-producing regions or even the decrease in production, from the cause of the transition to renewable energy resources. With the further advancement of globalization and the rapid development of international links, the shock transmission effect in the current turbulent times is characterized by the instability of oil prices and fluctuations in share prices on the stock market.

The motivation that made me choose this topic is to observe how important the oil price fluctuation is and how this influences the stock markets. In recent years, the analysis of the connections between economic and financial markets is of particular importance for investors in risk hedging strategies and portfolio diversification.

The importance of the paper "Oil and stock markets in ongoing flux: Impact of current events on oil price and stock market" using the DCC-GARCH model consists not only in the fact that it explores the complexity of the relationships between Brent Oil, the Baltic Dry Index and the main indices of the regional stock markets and Western Europe, but also provides significant contributions to the understanding of the functioning of these relationships and how they can affect

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the financial world, helping to develop better investment risk management strategies. The choice to analyze the influence of the oil market on the stock market in this paper can bring unique perspectives and valuable contributions to the deeper understanding of the need for the balance given by demand and supply on the oil market, as well as understanding the impact of the reduction of oil exploitation and the use of renewable resources, which have an effect on the economy and financial markets, including stock markets.

With all the renewable energy resources used up to now, oil still has a special importance in the economy, and its price fluctuations do not remain imperceptible on the financial market, on the contrary, these fluctuations are transmitted to the actions of the stock market indices and even to the behavior of the financial market in general. Therefore, it is observed that high oil prices have a direct and negative impact on the economy, even if, in many cases, there is a small correlation between oil price fluctuations and stock market shares.

The choice of Brent Oil, Baltic Dry and stock market indices from Romania, Poland, France, Germany, and Austria has several important reasons, including understanding the variability and complexity of the oil market, as well as its influence on both performances of the stock market indices chosen for analysis as well as on the bulk shipping index.

In recent years, the economy has faced a series of unfortunate events, known as "black swan" events, as analyst Taleb (2007) calls them, which are unpredictable, rare events with significant consequences and considered inevitable and difficult to anticipate.

The novelty of this work is given by the fact that it can help investors to better understand the risk associated with these assets by using econometric models developed to highlight the conditioned volatility. By applying the univariate GJR-GARCH model, which differs from the other models in the GARCH family, two important coefficients could be observed: the coefficient of the leverage effect and the asymmetry component. The results of the two coefficients show that there is a strong asymmetry in the response of conditional volatility to positive and negative shocks. The response of volatility to different types of shocks is significantly different, thus illustrating a contrast with how volatility increases following the propagation of a positive shock compared to its response to a negative shock.

Using the dynamic DCC-GARCH model (Dynamic Conditional Correlation GARCH model) the simultaneous modeling of the correlations between the analyzed indices was obtained and at the same time the conditional volatility could be modeled through the components of the GARCH model included in DCC-GARCH. By using this model, we want to highlight the changes in the level of correlations between the Brent Oil index, the Baltic Dry Index and the analyzed stock indices, considering the conditional volatility of each index. The contribution of the work to the literature in this field is the highlighting of the oil price fluctuations and its impact on the stock markets in periods when unexpected economic events of the "black swan" type take place. Thus, after analyzing the data, the biggest fluctuations in the price of oil affect the stock market at the beginning of the COVID-19 pandemic, while the biggest fluctuations in the Baltic Dry Index take place at the beginning of the military conflict between Russia and Ukraine.

This paper focuses on the volatility of Brent Oil prices, the Baltic Dry Index (BDI) and stock indices, from the Romanian stock market (BET index), the Polish stock market (WIG index), the French stock market (CAC40 index), the German stock market (DAX index) and the Austrian stock market (ATX index). The analysis covers a period of approximately 5 years (January 2019 - November 2023), and the results obtained in accordance with previous research confirm the presence of volatility in these markets. In the context of the negative events that have affected the global economy in recent years, the paper provides a detailed perspective on how the volatility of the oil market can affect the performance of financial markets, by analyzing the complex relationships between oil prices, the Baltic Dry Index (BDI) and the selected stock indices.

To pursue the proposed goal, the work is divided into literature review, methodology, results and discussions and conclusions.

Literature review

The specialized literature is vast in this field of knowledge. The work of Degiannakis, Filis and Arora (2019) focuses on the complex relationship between oil price fluctuations and their impact on the stock markets, and the significant results obtained show the essential interconnections between the variables considered. The results of this research show that oil volatility has a significant effect on stock markets, and oil price variations are transmitted to the stock market, thus creating a strong link between these two fields. This study adds to existing knowledge in the field and strengthens the understanding of how these two components of the global economy interact and influence each other. The specialized literature is vast in this field of knowledge.

The study by Managi, Yousfi, Zaied, Mabrouk and Lahouel (2021) highlights how the COVID-19 pandemic, a "black swan" event, has a significant influence on the financial market and brings a new perspective on the relationship between the oil market and the stock market, through the impact of the COVID-19 pandemic. The authors observe a significant difference between the volatility transmitted from the oil market to the stock market before the COVID-19 pandemic. The volatility transmitted during the pandemic is much higher than in the past and this is due to multiple causes, among which we can identify the uncertainty that comes from the uncertainty of the evolution of the virus, the lockdown measures with a large economic impact, the sudden and significant change in environmental conditions, context that led to changes in the way markets interact.

The research carried out by Kilian and Park (2009), highlights the main role of adjustment when there are significant changes in the oil market, in demand or supply. The authors study the influence of oil price fluctuations on the world oil market and show through the obtained results that the price variations are often generated by the shocks caused by the demand and supply of oil, which are proportionally transmitted to the stock market. The obtained results and the conclusions of this paper highlight that reducing the demand or supply of oil, acts as an effective adjustment mechanism and leads to the stabilization of the market following shocks, because although there is high volatility in the market in the short term, following shocks of demand or supply, the market adapts relatively quickly and returns to equilibrium.

Using, for stock market forecasting and accuracy, the DCC-GARCH model, as well as the model's applications, especially the value-at-risk calculation, Andersson-Säll and Lindskog (2019) obtained important results. The research is based on the model's ability to capture significant changes, to show the volatilities of the stock market and its correlations, and to use the DCC-GARCH model in the calculation of VaR (value at risk). It is observed that the way in which this model is applied in VaR calculation provides a robust method in risk estimation and highlights the usefulness and effectiveness of the econometric model in stock market forecasting and risk evaluation.

The study by Joo and Park (2021) using the application of quantile regression provides a detailed and specific insight into how oil price volatility can affect the performance of stock markets. Quantile regression, a statistical method that examines the relationship between variables, focuses on the quantiles of the distribution of the dependent variable. The results of the study highlight the asymmetric effects of oil price fluctuations on stock market shares, which means that oil price fluctuations can influence stock markets unevenly, depending on the direction of volatility changes, with different consequences.

By studying the interdependence between oil and stock markets, together with other assets, and using the bivariate and multivariate wavelet technique, Mensi et al. (2022) demonstrated that both the price of oil and the prices of shares on the stock exchange during periods of crisis or the Covid-19 pandemic registered an increased volatility. The results of the study show that the increased volatility of oil prices during periods of crisis and during the COVID-19 pandemic is correlated with increased volatility of stock prices on the stock market, and the wavelet theory is the one that can allow an interdependence analysis at the time and frequency level, providing a detailed understanding of how asset classes interact. The authors showed that events, such as crises or pandemics, can generate significant changes in market volatility and attract the attention of investors in making decisions in this context.

Binkley and Young (2021) in their study on the development of agricultural production used the Chow test (Chow, 1960) as a method of testing the differences in regression response between groups, and showed that if there are systematic differences, the Chow test is compromised.

Giacometti et al. (2023) in their study on financial effects uses multivariate GARCH models wanting to show the transmission of risk in banks from stock returns. Using a spatial DCC-GARCH model, they've demonstrated that the conditional variation of the log-returns of each bank depends on the shocks of past volatility of other banks and their parsimonious past squared returns.

Methodology

In order to observe the impact of recent events on the financial market and especially the evolution of the stock and oil markets, we've used in the analysis a database with daily frequency over a period of approximately five years (January 2019 – November 2023), which includes: the price of oil, the Baltic Dry Index (BDI) as well as representative stock market indices of Central and South-East European countries, such as: the Romanian index (BET) and the Polish index (WIG) but also indices of Western European countries, such as the French index (CAC40), the German index (DAX) and the Austrian index (ATX). The data was collected from international platforms such as Reuters and Yahoo Finance and, based on the prices of the stocks, the returns were calculated using the logarithmic formula. The working method by which the fluctuation of the oil price and the performance of the stock indices are followed starts from the results obtained for the most significant descriptive statistics, as well as from the results of the stationarity tests and the tracking of the stability of the parameters, for which we've used the Chow test (1960). This test involves dividing the original data sets into two or more approximately equal sub-samples with respect to the parameter t, which is chosen to be the dates: 3/09/2020; 2/24/2022 and 10/09/2023.

The hypotheses of the test are: H_0 (there are no structural changes at the breaking points - parameters are stable) and H_1 (there are structural changes at the breaking points - parameters are not stable). The characteristic equation of the test is:

$$CHOW\ F\ statistic = \frac{\frac{RSSp - (RSS_1 + RSS_2)}{k}}{(RSS_1 + RSS_2)/(N_1 + N_2 - 2\,k)} \tag{1}$$

where: $RSSp$ represents the combination of linear regression; RSS_1 represents the regression line before the break and RSS_2 represents the regression line after the break.

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The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models were introduced for the first time by Engle and Sheppard (2001), being an extension of the ARCH (Autoregressive Conditional Heteroskedasticity) models developed by Engle (1982) to model and forecast the conditional volatility of time series. Engle (1982) introduced ARCH models in which the variance conditioned by past information shows that it is not constant and depends on the square of previous innovations and Bollerslev (1986) generalized the ARCH models and recommended GARCH models in which the conditional variance does not depend only on the squared disturbances. Initially, the developed GARCH models were in univariate form, which means that they do not allow the determination of volatility for several variables simultaneously, nor do they allow the determination of correlations between variables. There are a variety of models included in the univariate GARCH family, among which we mention: the GARCH (1,1) model, GJR-GARCH (Generalized Joint Autoregressive Conditional Heteroskedasticity), IGARCH (Integrated GARCH), EGARCH (Exponential GARCH), TGARCH (Threshold GARCH), APARCH (Asymmetric Power ARCH). All these models are extensions of the GARCH (1,1) model, developed with the aim of reducing the limitations imposed by the previous model and for a better capture of volatility. These models differ from each other either by adding additional terms to capture the asymmetry or sudden events on the market or by improving the volatility capture method.

After the development of the univariate GARCH models, the multivariate GARCH models followed (Engle, 2002) which are part of the same GARCH family, being extensions of the GARCH models with the property that they can simultaneously analyze several data series and can capture the volatility and influence between the data series analyzed. Among these models are the DCC-GARCH (Dynamic Conditional Correlation GARCH) and CCC-GARCH (Constant Conditional Correlation GARCH) models.

In the analysis carried out in the paper, we applied the univariate GJR-GARCH model as well as the multivariate DCC-GARCH model. The choice of these models was motivated by the intention to highlight the asymmetry and the change in the behavior of the conditional variability depending on a threshold price being exceeded by using univariate GARCH models (such as the GJR-GARCH model), but also by the aim to showcase the influence among the analyzed variables. The GJR-GARCH (Generalized Joint Autoregressive Conditional Heteroskedasticity) model is a univariate model that is part of the GARCH family, and its main characteristic is the integration of an additional term to capture asymmetry, in response to positive and negative news.

The characteristic formula in the generalized form of the model is:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} (\alpha_i + \gamma_i I_{t-1}) * \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

where: α, γ, β represent the constant parameters, and I is a dummy variable (indicator function) that can take the value 0 (respectively 1) if ε_{t-i} is positive (respectively negative). If the estimates, $\gamma > 0$, then negative errors have a leverage effect. It is assumed that all model parameters are positive and $\frac{\alpha+\beta+\gamma}{2} < 1$.

The multivariate DCC-GARCH model, as described by Engle (2002) is characterized by a DCC estimator that differs from the CCC-GARCH model estimator developed by Bollerslev (1990) only in that it allows the correlation matrix R containing the correlation conditional to vary over time. The characteristic formula is:

$$H_t = D_t R_t D_t \tag{3}$$

Orskaug (2009) starting from the work of Engle (2002) highlighted the component elements of the matrix D_t, matrix that represents the standard deviation of the GARCH model and is characterized by the formula:

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{nt}} \end{bmatrix} \tag{4}$$

The decomposition of R_t characteristic of the DCC-GARCH model consists in:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5}$$

$$Q_t = (1 - a - b)\bar{Q} + a\epsilon_{t-1}\epsilon_{t-1}^T + bQ_{t-1} \tag{6}$$

where: parameters a and b are two parameters with a numerical value and $\bar{Q}$ represents the unconditional covariance matrix of the standard errors ϵ_t and is characterized by the formula:

$$\bar{Q} = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t \epsilon_t^T \tag{7}$$

and the diagonal matrix, whose diagonal elements are its square root and Q_t is characterized by the formula:

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \ldots & 0 \\ 0 & \sqrt{q_{22t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{q_{nnt}} \end{bmatrix} \tag{8}$$

The analysis carried out shows that during the COVID-19 pandemic, oil prices suffered significantly higher fluctuations compared to the period covering the ongoing military conflicts. In this last period, no significant influence of the oil price on the stock market was observed, however, the capital markets remained interconnected and, in Figure 1, it can be seen the evolution of the returns of the stock markets and oil during the analyzed period.

In Figure 1 we've graphically illustrated the evolution of the returns with daily frequency of the capital markets, as well as of the oil market, and the transport of bulk goods in the analyzed period January 2019-November 2023. Following the resulting graphs, a high volatility can be observed among the returns of the markets analyzed.

Variations in the price of oil lead to variations in the prices of the stock market indices and affects investment portfolios, an observable fact on the oil market during the COVID-19 pandemic when major changes took place, which generated a decrease in the demand for oil and created an imbalance in the market because of the closure of industries and of decreased mobility during the isolation period. Keeping oil production at the same level during the first stage of the Covid-19 pandemic led to an oversupply in the market, which led to a significant drop in oil prices in April 2020 as storages filled up.

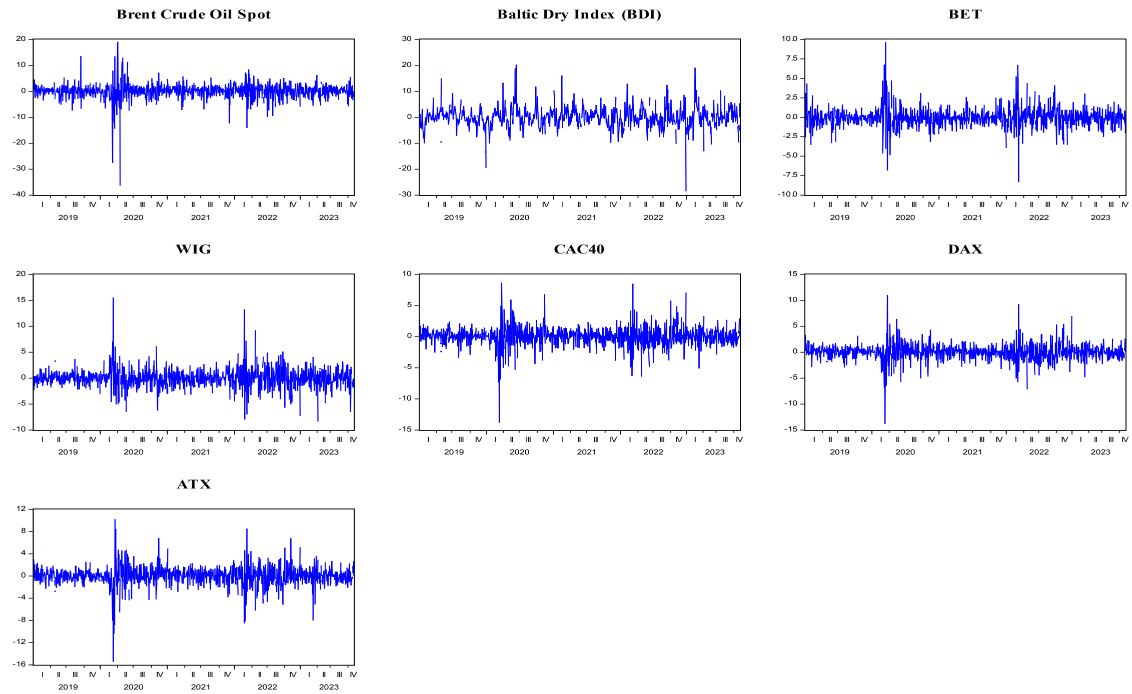

Figure 1. The evolution of returns of the data series

Source: Author's own calculations, based on data available on Reuters platform.

Through the analysis carried out, the COVID-19 pandemic, the war between Russia and Ukraine, as well as the war between Israel and Hamas, are analyzed and the graphs illustrate that certain countries were affected more during the COVID-19 pandemic period than they were affected following the outbreaks the two military conflicts. For example, the price of oil was strongly affected (observable by the drastic decrease in yield) by the start of the pandemic, while the Baltic Dry Index was strongly affected by the start of the war between Russia and Ukraine because at the time when the war started, the uncertainty of the transport of goods by sea also appeared. Most of the capital markets, as the graphs show, were affected more by the COVID-19 pandemic and less by the war between Russia and Ukraine that started in February 2022.

Table 1. The correlation coefficient between the analyzed variables

	Brent Oil	BDI	BET	WIG	CAC40	DAX	ATX
Brent Oil	1.00						
BDI	0.02	1.00					
BET	-0.19	0.02	1.00				
WIG	-0.21	0.06	0.60	1.00			
CAC40	0.23	-0.07	-0.65	-0.75	1.00		
DAX	0.20	-0.06	-0.65	-0.76	0.96	1.00	
ATX	0.28	-0.06	-0.63	-0.74	0.87	0.86	1.00

Source: Authors' own research.

Regarding the correlation coefficient, there are weak correlations (positive and negative) between oil price returns and stock index returns, but, as can be seen from Table 1, a significant degree of correlation can be observed between the stock markets.

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Results and discussions

Descriptive statistics help to better understand the data and their trends. They provide an overview of the characteristics of the data sets by using certain statistical and econometric indicators such as: mean, standard deviation, skewness, kurtosis, that lead to a better understanding of the data series and even to possible adjustments in the database (for example suppressing unnecessary observations).

Table 2. Results of descriptive statistics and stationarity test

Variables	Mean	StdDev	Kurtosis	Skewness	Min	Max	ADF (prob)
Brent Oil	0.03	3.02	28.26	-2.07	-36.41	19.08	0.00
BDI	0.03	3.84	5.83	0.12	-28.53	20.34	0.00
BET	-0.05	1.25	8.62	0.64	-8.34	9.65	0.00
WIG	-0.01	1.81	9.33	0.80	-8.40	15.55	0.00
CAC40	0.04	1.54	9.98	-0.61	-13.85	8.67	0.00
DAX	0.03	1.56	10.52	-0.38	-13.80	11.03	0.00
ATX	0.01	1.73	11.09	-0.93	-15.42	10.24	0.00

Source: Authors' own research.

From Table 2, on average, most of the stock indices (except for BET and WIG) record an increase in yield over the selected period. The results obtained after the application of the standard deviation shows in the data a high volatility (especially in the case of oil) generated by the events that affected the global economy. From the perspective of the skewness and kurtosis coefficients, it can be said that the data come from platykurtic distributions with values greater than 3 and, in most cases, it can be observed a negative asymmetry (exception: the BDI, the BET index, and the WIG index). The minimum and maximum values come as a confirmation of what was mentioned above because the minimum of the Brent Crude Oil index coincides with the start date of COVID-19 pandemic (16/04/2020) and the minimum of the BDI coincides with the war period between Rusia and Ukraine (23/12/2022). The probability of the ADF test (1976) shows that the data series with a probability that does not exceed the threshold of 0.05 are statistically significant.

The Chow test (1960), also known as the "Chow Breakpoint Test", has the role of identifying structural changes in at least one of the breakpoints chosen in this paper. These breakpoints represent the dates when significant events occurred. They are chosen to assess whether these events had a major impact on the global economy.

Table 3. Chow test results

Chow Breakpoint Test: 3/09/2020 2/24/2022 10/09/2023			
Null Hypothesis: No breaks at specified breakpoints			
Varying regressors: All equation variables			
Equation Sample: 1/03/2019 11/03/2023			
F-statistic	3.995628	Prob. F(21,1105)	0.0000
Log likelihood ratio	82.92434	Prob. Chi-Square(21)	0.0000
Wald Statistic	83.90819	Prob. Chi-Square(21)	0.0000

Source: Authors' own research.

Analyzing the F-statistic, we've notice that the value is high, which leads us to reject the null hypothesis and, from the results of the probabilities, we can confirm the existence of a significant change in the relationship between the studied variables at the three breaking points (which comes as a confirmation that the recent events had a strong impact on financial markets). The breaking points were carefully selected because they represent the start date of the COVID-19 pandemic and the start date of the two military conflicts. To verify the results obtained by the Chow test, we will first test the univariate GJR-GARCH (1,1) model and then the multivariate DCC-GARCH (1,1) model.

Table 4. Results of the GJR-GARCH (1,1) model

GJR-GARCH Param.		**Coeff.**		**Coeff.**		**Coeff.**		**Coeff.**
μ		0.25***		-0.16		-0.09***		-0.07
AR (1)		-0.35***		0.53***		-0.10		0.75***
MA (1)		0.39		0.23***		0.17		-0.69***
ω	Brent	0.24***	Baltic	5.18***		0.04***		0.03***
α_1	Crude	0.12***	Dry	0.40***	BET	012***	WIG	0.03***
β_1	Oil	0.84***	Index	0.12		0.85***		0.93***
γ_1		-0.52***		0.02		0.27***		0.99***
δ_1		4.82***		3.38***		4.85***		5.18***
Loglikelihood		-2523.231		-2657.177		-1622.347		-2086.076
μ		0.11***		0.09***		0.10***		
AR (1)		-0.03		0.72		0.60***		
MA (1)		0.05		-0.72		-0.54***		
ω		0.03***		0.04***		0.06***		
α_1	CAC40	0.05***	DAX	0.05***	ATX	0.06***		
β_1		0.89***		0.90***		0.88***		
γ_1		-0.99***		-0.99***		-0.99***		
δ_1		5.39***		4.68***		5.94***		
Loglikelihood		-1848.246		-1864.944		-1963.514		

**** significant at 1%, ** significant at 5% and * significant at 10%.*

Source: Authors' own research.

From the results obtained for most of the data series used, the volatility coefficients observed, one in front of the ARCH effect (α_1) and one in front of the GARCH effect (β_1), are positive, their sum having values between 0 and 1, which means that the theory regarding $\alpha + \beta < 1$ is respected. It cannot be said the same, in the case of the Baltic Dry Index, which presents a statistically insignificant β_1 coefficient.

The difference between the univariate GARCH model and the rest of the models developed later is that each new model created brought an improvement to the old model. For example, in the GJR-GARCH model, a new element called the leverage effect appears and is represented by the coefficient γ_1. Thus, this leverage effect shows the impact produced by asymmetric shocks, which can be both positive and negative on conditioned volatility. According to the results obtained from Table 4, it can be observed that, in the case of the BET and WIG series, the coefficient is greater than 0, which is statistically significant and respects the relationship by which $\gamma_1 < 2 - \alpha - \beta$. In the case of oil and the stock indices: CAC40, DAX and ATX, a negative coefficient can be observed, which is statistically significant and respects the previously exposed relationship through which $\gamma_1 < 2 - \alpha - \beta$. A significantly positive leverage means that there is a strong asymmetry in the response of conditional volatility to positive and negative shocks. The response of volatility to the different types of shocks is different, thus illustrating a contrast between how volatility increases following the propagation of a positive shock and its response to a negative shock, and this asymmetry is different in the case of a negative asymmetric leverage effect. In such a scenario, the positive coefficient indicates that, following a positive shock, conditional volatility will increase more than after a negative shock of the same magnitude. A positive asymmetric leverage effect shows that the two stock markets represented by the BET and WIG indices are more sensitive to increases than to decreases of the same magnitude. In other words, the reaction of the two markets is much stronger if prices suddenly increase following the propagation of a positive shock compared to the case of a negative shock, where the volatility will register a smaller increase, which can be seen from Figure 1, where it is shown how the two stock markets reacted strongly in the first quarter of 2020 to the outbreak of the COVID-19 pandemic in Europe. The series: Brent Oil, CAC40, DAX and ATX presents a coefficient of the leverage effect, negative and significant, which means that the oil market, as well as the three stock markets, reacts much more strongly to price drops following significant events. Thus, a sudden drop in the price (following the appearance of a negative shock) will produce an increase in the level of conditioned volatility higher than in the case of a positive shock (something also observable in Figure 1, where in the first quarter of 2020 after the outbreak of the pandemic COVID-19, the markets had a drastic drop in prices).

Another characteristic coefficient of the GJR-GARCH (1,1) model is the asymmetry component (δ_1) of the volatility, which illustrates the magnitude of the asymmetric leverage effect resulting from extreme events (for example the market shocks caused by the outbreak and spread of the COVID-19 pandemic or the two military conflicts). Following the results obtained, it can be observed that this coefficient registers positive and significant values for all the time series used, which shows a significant extent of the asymmetric leverage effect. The registered values of the coefficient (δ_1) are quite pronounced, which highlights a more pronounced asymmetry of markets in responses to shocks.

Table 5. Results of the DCC-GARCH (1,1) model

DCC-GARCH Param.		**Coeff.**		**Coeff.**		**Coeff.**		**Coeff.**
μ	BET	-0.08***	WIG	-0.03	CAC40	0.06	DAX	0.04
AR (1)		-0.10		0.80***		0.54		0.92***
MA (1)		0.17		-0.74***		-0.54		-0.93***
Ω		0.03***		0.03		0.06		0.04
α_1		0.11***		0.07***		0.11***		0.10***
β_1		0.87***		0.92***		0.87***		0.89***
μ	ATX	0.04	Brent Crude Oil	0.15***	Baltic Dry Index	-0.07	DCC	
AR (1)		0.66***		-0.88***		0.55***		
MA (1)		-0.62***		0.89***		0.22***	α	0.02***
Ω		0.05		0.22*		3.93***	β	0.95***
α_1		0.12***		0.15**		0.21***	Log-likelihood	
β_1		0.87***		0.84***		0.34***	-12349.84	

***** significant at 1%, ** significant at 5% and * significant at 10%.*

Source: Authors' own research.

As in the case of the univariate model and in the case of the bivariate GARCH model, we can observe the volatility coefficients, one in front of the ARCH effect (α_1) and the one in front of the GARCH effect (β_1), both coefficients being positive, their sum having values between 0 and 1, which means that the theory regarding $\alpha + \beta < 1$ is respected.

Following the results obtained, the parameters $dcc\alpha$ şi $dcc\beta$ measure the degree of interdependence between the analyzed time series and the conditional time variation of the covariance between them. The parameter $dcc\alpha$, with a statistically significant value of 0.02, highlights a low impact of past extreme events on current volatility, while the parameter $dcc\beta$, with its statistically significant coefficient of 0.95, shows a persistent conditional volatility of the covariance between the series and its high value tends to hold over time.

Conclusion

The major impact on the global economy of the events that have happened in recent years, including the returns of stock indices and the price of oil, is mainly due to the uncertainty in the medical, political, and economic fields, which has led to a low feeling of investors and reserved investments. Besides this, factors such as: the limitation of oil resources, the effects of global warming, the renewable resources used that do not cover the needs of society, are just some of the problems necessary to adopt new strategies in the energy field and the use of oil.

In conclusion, it can be said that the decrease in the demand for oil, which automatically affects the price of oil, was caused not only by these factors but also by the COVID-19 pandemic, when the volatility of the oil price reached maximum levels, which strongly influenced the capital markets. There is also the impact of the military conflict between Russia and Ukraine, which greatly affected the Baltic Dry Index (BDI) due to the disruption of shipping and the economic uncertainties generated by the conflict. However, the military conflict generated a smaller impact on oil prices and stock indices. The negative events that happened in recent years (the "black swan" type) showed, according to the results obtained, the existence of interconnections between Brent Oil prices, the Baltic Dry Index (BDI) and various European stock market indicators such as those on: the Romanian stock market (BET index), the Polish stock market (WIG index), the French stock market (CAC40 index), the German stock market (DAX index) and the Austrian stock market (ATX index). The correlation coefficient showed through the generated results that there are strong positive and negative correlations between stock markets and weaker correlations between oil and markets. From the perspective of stock indices such as BET (Bucharest Stock Exchange), WIG (Warsaw Stock Exchange Index), CAC40 (Paris Stock Exchange Index), DAX (Frankfurt Stock Exchange Index), and ATX (Austrian Stock Exchange Index), the results showed that the indices recorded, on average, both positive and negative returns. This aspect denotes an instability at the level of the markets and an increased sensitivity to the events that have taken place in recent years worldwide. The significant volatility associated with indices such as BDI (Baltic Dry Index) and Brent Oil highlight significant price fluctuations. It can be said that unfavorable events have a strong impact on the analyzed stock market indices but also on the Brent Oil and Baltic Dry Index, which can be seen from the results obtained by applying the DCC-GARCH model. Applying the Chow test, we've noticed the existence of a significant change in the relationship between the studied variables at three breaking points (3/09/2020; 2/24/2022; 10/09/2023), which comes as a confirmation that the recent events had a strong impact on financial markets.

Even if there is no strong correlation between the price of oil and the stock indices, the existence of interconnections between the markets makes the fluctuations of the price of oil indirectly evident through the impact on the costs and profitability of companies. Thus, the indirect influences of oil prices on costs and economic performance can have repercussions on financial markets and investor behavior.

References

Andersson-Säll, T., & Lindskog, J.S. (2019). A STUDY ON THE DCC-GARCH MODEL'S FORECASTING ABILITY WITH VALUE-AT-RISK APPLICATIONS ON THE SCANDINAVIAN FOREIGN EXCHANGE MARKET. *Economics*, 2019.

Binkley, J.K., & Young, J. (2018). The Chow Test with Time Series-Cross Section Data. *Social Science Research Network*.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31, 307-327.

Bollerslev, T. (1990). Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model. *The Review of Economics and Statistics*, 72 (3), 498-505.

Chow, G.C. (1960). Tests of Equality Between Sets of Coefficients in Two Linear Regressions. *Econometrica*, 28(3), 591-605.

Degiannakis, S., Filis, G., & Arora, V. (2018). Oil Prices and Stock Markets: A Review of the Theory and Empirical Evidence. *The Energy Journal, International Association for Energy Economics*, 39(5).

Engle, F.R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), 987-1007.

Engle, F.R., & Sheppard, K. (2001). Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH. NBER Working Paper: No. w8554.

Engle, F.R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics*, 20(3), 339-350.

Fuller, W.A. (1976). *Introduction to Statistical Time Series*. New York: John Wiley and Sons.

Giacometti, R., Torri, G., Rujirarangsan, K., & Cameletti, M. (2023). Spatial Multivariate GARCH Models and Financial Spillovers. *Journal of Risk and Financial Management,* 16(9):397.

Joo, Y.C., & Park, S.Y. (2021). The impact of oil price volatility on stock markets: Evidences from oil-importing countries. *Energy Economics*, 101(2021), 105413.

Kilian, L., & Park, C. (2009). The Impact of Oil Price Shocks on the U.S. Stock Market. *International Economic Review*, 50(4), 1267-1287.

Managi, S., Yousfi, M., Zaied, Y.B., Mabrouk, N.B., & Lahouel, B.B. (2022). Oil price, US stock market and the US business conditions in the era of COVID-19 pandemic outbreak. *Economic Analysis and Policy*, 73, 129-139.

Mensi, W., Rehman, M.U., Al-Yahyaee, K.H., & Vo, X.V. (2023). Frequency dependence between oil futures and international stock markets and the role of gold, bonds, and uncertainty indices: Evidence from partial and multivariate wavelet approaches. *Resources Policy, Elsevier,* 80(C).

Orskaug, E. (2009). Multivariate DCC-GARCH Model-With Various Error Distributions. Norwegian University of Science and Technology.

Taleb, N.N. (2008). *The black swan: the impact of the highly improbable*. New York: Random House.