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FINANCIAL MARKET INTERCONNECTIONS ANALYZED USING GARCH UNIVARIATE AND MULTIVARIATE MODELS

Abstract. *Given that the financial markets are facing the effects of the coronavirus pandemic, we chose to perform an analysis on them, in order to see the transmission of volatility, the effects of the contagion and the interconnection between the financial markets. Using stock indices from different countries and applying theoretical and empirical methods such as univariate and multivariate models (ARCH–GARCH, BEKK), we aim to capture volatility and bidirectional contagion, as well as testing and occurring the phenomenon of clustering volatility and its transmission effect.*

Keywords*: Volatility, Contagion, Clustering, ARCH–GARCH models, GARCH–BEKK models.*

JEL Classification: C01, C12, C31, C32, C38, C58, C61, F47

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1. Introduction

This work, carried out using econometric methods, studies the real and nominal interconnections of the capital market, which can act as a buffer for the economy against shocks, or as a mechanism for their propagation and even amplification. For the purpose of the proposed analysis we used stock indices from several countries, such as: USA (S&P500; DJI30; NQ100), UK (FTSE100), Switzerland (SMI20), Netherlands (AEX25), Germany (DAX30), France (CAC40), Czech Republic (PX), Poland (WIG) and Romania (BET), tracking, in the current context the occurrence and transmission of volatility, the phenomenon of contagion and the existence of shocks and their impact between one stock exchange to another.

The importance of the paper is due to capturing the effects of contagion and shocks and the transmission of volatility on financial markets, starting from the fact that stock markets anticipate the evolution of the main economic indicators. Stock markets are connected by investors who diversify their portfolio by choosing several stock exchanges for trading, as well as by the fact that in the contemporary era there are transactions on the stock markets based on instruments capable of analyzing statistical phenomena and executing orders at very high speeds, which are even taking advantage of small price differences in stocks, where there is contagious volatility, so, therefore, shocks that are occurring due to the interdependence between the markets. What makes this paper new compared to other papers in this field is that it highlights the contagion of the stock markets and illustrates the significant increase in the correlation between stock indices in different European countries with different degrees of development and the American market, as well as the transmission of volatility from the American market to the European market. Behavioral finance studies on the spreading effect of volatility on financial markets show that news is transmitted not only from one stock exchange to another, but also between the macroeconomic levels of different countries, affecting the value of financial assets, leading to real economic growth or decline between states. Although the topic of contagion and volatility has been debated since a few decades ago, when ARCH models (Engle, 1982) had a variation dependent on the square of previous innovations and GARCH models (Bollerslev, 1986) whose conditioned variation did not depend only on the square of the perturbations, this is a current topic because contributions are made by analyzing the new situations encountered.

The treated subject is accompanied by novelties brought in the field, being an improvement on the previous works. Ding, Granger, and Engle (1995) introduced the APARCH (asymmetric power ARCH) model, in which two parameters based on the GARCH model were developed, one of which is used as a lever measure. The detection and modeling of structural changes in GARCH processes has attracted increasing attention in time series econometrics according to Brooks (2019). The use of the ARCH model is one of the ways in which a phenomenon of this nature can be parameterized and the GARCH model allows the conditioned variant to depend on its own lags enough to capture the evolution of volatility. Information on a stock market spreads rapidly among other markets and, with it, its volatility is transferred, the effect being known as propagation effects, an important phenomenon due to the increase of correlation coefficients between stock market returns and the appearance of effects that are transferred between financial assets listed on various stock exchanges. The phenomenon of grouping volatility, caused by the continuous effect of external shocks, is known as volatility clustering and the ARCH model explains the regularity of time series and yields, while the GARCH model explains the heteroskedasticity of residues in the yield sequence.

2. Literature review

As is clear from the vast literature in the field, the works that debate topics about contagion and volatility are a topic that always brings an improvement to previous works. Haque et al. (2004) shows the evolution of stocks by using GARCH models on the series of weekly returns from different markets, among which they discovered the correlation between them. Box and Jenkins (1976) performed an univariate analysis by using ARCH and GARCH models on exchange rate time series to capture asymmetry in grouping volatility and leverage.

Another applicability of GARCH models is found in the work of Matamoros and Dala (2021) which, by using modeling the volatility of the series of daily observations of foreign exchange, obtained the conversion of one currency into another at a certain known exchange rate.

Elgammal, Ahmed and Alshami (2021) are bringing through their study a clearer view on the level of connection between different stock markets, bonds, commodities, both in terms of returns and volatility. The results obtained using a GARCH bivariate model show that the transmission effect of returns is bidirectional between stock markets and unidirectional between energy markets and gold markets. Hung (2020), by using the GARCH–BEKK model, studies the frequency over time of the spillover effect on different stock markets and the empirical results obtained showed a clear existence of the spread of volatility, as well as correlations between the different markets studied.

Spulbar et al. (2020) investigated the existence of volatility spillovers based on symmetric and asymmetric GARCH models such as EGARCH and GJR from January 2000 to June 2018 for a cluster of international emerging and developed stock markets. Moreover, Trivedi et al. (2021) examined the presence of volatility clustering, correlation and comovements between certain emerging and developed European stock markets by using GARCH family models from January 2000 to July 2018.

As shown in Stan et al. (2020), the contagion between the stock markets and the effects of the pandemic, created an instability on the market, which affects the decisions and actions adopted by managers. The connections between the stock markets are well known in the literature. With the emergence of the pandemic, complex crises were created with an unlikely impact, the understanding of which took time, as illustrated in Brătianu (2020). Hansen (2021) shows how financial contagion is often defined as the spread of shocks between market players, while the correlation and excessive interconnectivity of markets, actors or investment strategies are seen as reasons for its spread. The authors concluded that, during the pandemic, the correlations and the effect between the different financial markets is greater than it would normally be.

3. Research methodology

3.1. Data description

In this paper, in order to highlight the effect of contagion and the transmission of volatility on financial markets, we used data sets with daily observations (5 days a week) between November 7, 2016 - November 3, 2021, based on the closing prices of the stock indices: USA (S&P500, DJI30, NQ100), Great Britain (FTSE100), Switzerland (SMI20), Netherlands (AEX25), Germany (DAX30), France (CAC40), Czech Republic (PX), Poland (WIG) and Romania (BET). Before starting the analysis, the data series were adjusted so that we excluded the trading days that did not coincide, leaving only the transactions performed on the same trading days for the analyzed indices. Subsequently, the generation of each data series (i.e. the daily percentage variation) was performed by calculating the yield by using the natural logarithm, characterized by the formula: $P_t = ln(\frac{P_t}{P_{t-1}}) \cdot 100$, and the analysis, the effect of contagion and the grouping of volatility, as well as the transmission of shocks from one market to another and the persistence of these shocks on the analyzed markets, was performed based on the yields of the daily data series.

3.2. Stationary and normal series

The time series came out as being stationary after using the Augmented Dickey–Fuller and Kwiatkowski–Phillips–Schmidt-Shin stationary tests, The calculation formula of the ADF test is:

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \qquad (1)$$

where: α is a constant, β is the coefficient of a time trend and p is an order of the lag of the autoregressive process. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is based on the ADF model, but contrary to it, it shows that the absence of a unit root is not a proof of stationarity, but of stationary tendency. After testing the stationary of the time series used on the analyzed stock indices, the normality of the distribution is calculated by applying tests such as: Jarque–Bera and Kolmogorov-Smirnov, necessary to see if the series comes from a normal distribution. After the normal distribution of the series of stock indices, we test the appearance of the clustering phenomenon, which can also be seen as a test consisting of a set of input vectors, which initially does not correspond to any set of output vectors. The clustering of volatility is a phenomenon that is influenced mainly by economic and political factors, but also by the herd behavior of investors.

3.3 Error autocorrelation and ARCH-GARCH univariate models

Before addressing the topic of ARCH and GARCH models, it was first tested whether the series is stationary and then we tested the error autocorrelation using the Breusch–Godfrey, because the presence of autocorrelation indicates that more than one series can apply GARCH models. In this paper we've applied the following GARCH models: GARCH model (1,1), EGARCH (1,1) and APARCH, due to the fact that we want to see if the volatility coefficients meet the basic condition of the GARCH model and analyze the existence of leverage through the EGARCH and APARCH models.

3.4 BVGARCH (BEKK)

The transfer of volatility from one market to another is observed through the so-called volatility exit effects and, by using multivariate modeling, one can observe the inter-market influence of past shocks, past volatility on current volatility, Baba, Engle, Kraft, and Kroner (1989). This is the model that considers the temporary nature of conditional volatility and the correlation of stock markets. In addition, this model can predict future sales actions by taking into account the previous volatilities and shocks. We chose the BEKK model in bivariate form, due to the possible effects of transmitting volatility and the existence of a certain type of dynamics. BEKK is a multivariate model that presents a covariance variance matrix, or (var-covar) error matrix, estimated based on two other matrices, which quantifies the effect of shocks and volatility.

BEKK formula: $H_t = C_0'C_0 + A_{11}'\varepsilon_{t-1}\varepsilon_{t-1}'A_{11} + G_{11}'H_{t-1}G_{11}$ (2)

where: the interception of the matrix breaks down into $C_0'C_0$; C_0 is a smaller triangular matrix; $C_0'C_0$ is defined as semi-positive and A represents the effect of shocks on volatility, and G represents the impact of volatility on conditional variance.

4. Empirical findings

4.1. Descriptive statistics and minimum and maximum points

In this paper we've highlighted, in Table 1, the results obtained by applying the main descriptive statistics on the series of daily yields.

Considering the positive values of the yields for the last 5 years, it can be said that, on average, the price of stock indices on the stock markets tends to increase and, in terms of the obtained dispersion, each annual value deviates from the average.

Table 1: Descriptive statistics

Series	Mean	Standard deviation	Skewness	Kurtosis	Min	Max	Quantile	
							90%	99%
European stock market indices								
RFTSE100	0.005	1.101	-1.266	18.178	-11.512	8.666	1.033	2.551
RDAX30	0.037	1.258	-0.991	17.893	-13.054	10.414	1.283	3.292

RCAC40	0.039	1.229	-1.350	18.401	-13.098	8.056	1.209	2.802
RSMI20	0.042	0.984	-1.196	15.324	-10.133	6.780	1.037	2.344
RAEX25	0.053	1.102	-1.279	17.025	-11.375	8.590	1.126	2.496
RPX	0.036	0.949	-1.174	16.514	- 8.160	7.369	0.925	2.489
RWIG	0.038	1.211	-1.497	17.291	-13.526	5.633	1.365	3.364
RBET	0.056	1.099	-2.160	25.151	-11.892	6.690	1.022	2.505
American stock market indices								
RDJI30	0.061	1.306	-1.158	24.877	-13.841	10.764	1.167	3.136
RS&P500	0.070	1.247	-1.134	21.797	-12.765	8.968	1.134	3.076
RNASDAQ100	0.109	1.477	-0.769	10.978	-13.003	9.596	1.503	3.944

Source: Authors' work

Figure 1 shows the evolution of prices and yields of stock indices, observing the minimum and maximum points. The paper captures significant values in terms of minimum and maximum values recorded in the analyzed stock markets, which show the existence of negative impact events leading to the collapse of the global stock market on February 20 and ended on April 7, 2020, but also positive stock market events when maximum values have been recorded. Information on rising and falling indices, is collected from public information to show that the impact of events is transmitted from one market to another, almost simultaneously. Based on a global synchronized economic slowdown in 2019, the main reasons analysts pointed out were due to either liquidity issues or the US-China trade war, as well as global economic closures due to the February 2020 pandemic. There have been numerous severe daily declines in the global stock market, starting with 06.03.2020, when the reduction in travel demand and the inactivity of factories due to the COVID-19 pandemic significantly affected the demand for oil, causing the price to fall.

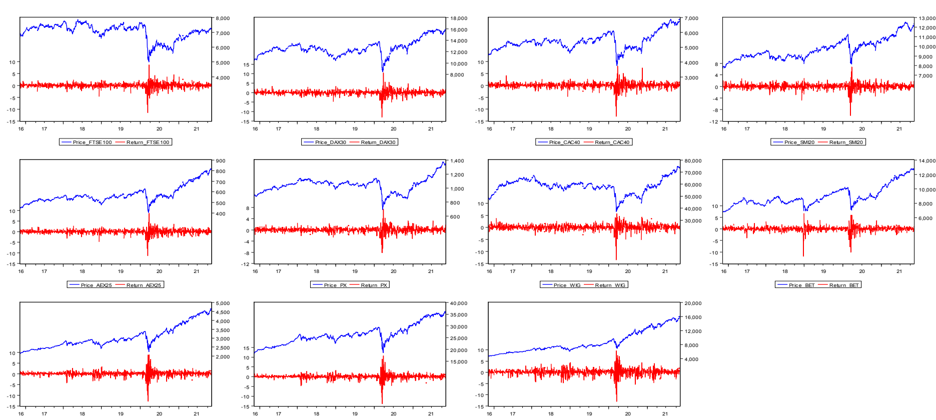

Figure 1. Evolution of prices and yields of stock indices

Source: Authors' work

In April 2020, Saudi Arabia and Russia agreed to reduce their oil production, but it can be seen how this event negatively affects all stock indices analyzed, as noted by the following values: BET (-1,57); WIG (-2,85); PX (-2,84); DAX30 (-3,43); FTSE100 (-3,69); CAC40 (-4,23); AEX25 (-3,92); SMI20(-4,09); DJI30 (-0,99), S&P500 (-1,72), NASDAQ100 (-1,64). On 09.03.2020, another significant decrease in stock markets observed based on the given results, took place, nicknamed "Black Monday I". It can be seen how this event negatively affects, instantly, all stock market indices analyzed, as follows: BET (-7,83); WIG (-7,80); PX (-5,27); DAX (-8,28); FTSE100 (-8,00); CAC40 (-8,76); AEX25 (-7,96); SMI20 (-5,71); DJI30 (-8,11), S&P500 (-7,90); NASDAQ100 (-7,07). On 11.03.2020, due to the immediate onset of the pandemic, the US and European stock markets closed, while the NASDAQ, S&P500 and Dow Jones indices also fell, and the pandemic countermeasures raise the upper level of overnight redemption. The decrease in the returns obtained from the analyzed stock market indices: BET (-3,98); WIG (-5,70); PX (-3,08); DAX30 (-0,35); FTSE100 (-1,41); CAC40 (-0,57); AEX25 (-0,27); SMI20 (-0,47); DJI30 (-6,03); S&P500 (-5,01); NASDAQ10 (-4,47) indicates the impact of this event on the stock markets and the transmission of information from one market to another. On 12.03.2020, on this date called "Black Thursday" there was a collapse of the stock market worldwide marked by a lack of confidence on the part of investors and the ECB, which decided not to cut interest rates despite expectations, leading to a very large drop in S&P500 futures. The decrease of the studied indices was: BET (-5,28); WIG (13,53); PX (-8,16); DAX30 (-13,05); FTSE100 (-11,51); CAC40 (-13,10); AEX25 (-11,38); SMI20 (10,13); DJI30 (-10,52); S&P500 (-9,99); NASDAQ (-9,73). On 13.03.2020, the European stock markets closed mostly on the rise, and the Dow Jones Industrial Average, the NASDAQ Composite Index and the S&P 500 rose as follows: WIG (3,87), PX (1,15); DAX30 (0,77); FTSE100 (2,43); CAC40 (1,82); AEX25 (0,17); SMI20 (1,17); DJI30 (8,95); S&P500 (8,88); NASDAQ100 (9,60); BET (-0,86).

On 16.03.2020, the Dow Jones, S&P500 index and the Nasdaq index fell significantly, and the stock markets closed, was the largest decline for the Dow Jones index, as shares in The United States and Europe have closed, noting how information is passed from the US stock market to other stock markets such as Germany and the Netherlands, along with stock markets such as Switzerland, France, Poland. and Romania registering values such as: BET (-10.08); WIG (-2,33); PX (-8,08); DAX30 (-5,45); FTSE100 (-4,09); CAC40 (-5,92); AEX 25 (-3,79); SMI20 (-1,69); DJI30 (-13,84); S&P500 (-12,77); NASDAQ100 (-13,00). On 18.03.2020, the US and European stock markets closed, while the NASDAQ, S&P500 and Dow Jones indices fell, reason why the New York Stock Exchange announced that it will temporarily close its transactions and will switch to electronic trading. This time the analyzed indices have the following values: BET (-3,63); WIG (-1,54); PX (-6,70); DAX30 (-5,72); FTSE100 (-4,13); CAC40 (-6,12); AEX25 (-4,87); SMI20 (-1,83); DJI30 (-6,51); S&P500 (-5,32);

NASDAQ100 (-4,08). On 20.03.2020, US and European stock markets closed for the most part, while the Dow Jones Industrial Average, NASDAQ Composite and S&P500 closed with the largest increase in the period. At this date, the analyzed indices have the following values: BET (1,25); WIG (4,30); PX (2,68); DAX (1,98); FTSE100 (1,39); CAC40 (2,65); AEX25 (4,51); SMI20 (5,18); DJI30 (0,94); S&P500 (0,47); NASDAQ100 (1,57). On 24.03.2020, as a result of G20 finance ministers and central bank managers, they agreed to develop a joint action plan to address the economic effects of the coronavirus pandemic and, at that time, global stock markets closed. The Dow Jones Industrial Average, NASDAQ Composite and S&P500 also rose to record heights. At this date, the analyzed indices have the following values: BET (5,97); WIG (2,69); PX (7,37); DAX30 (10,41); FTSE100 (8,67); CAC40 (8,06); AEX25 (8,59); SMI20 (6,78); DJI30 (10,76); S&P500 (8,97); NASDAQ100 (7,52). Even if the analyzed period is 5 years (November 7, 2016 - November 3, 2021), the minimum and maximum results mentioned above correspond to the crisis period caused by the COVID-19 pandemic and highlight the impact of the coronavirus pandemic on stocks. It can be observed how a negative shock, which is sufficiently strong on a market, is causing losses to that stock market, but also transmits these losses to the other stock markets. The information is transmitted through massive declines, starting with the collapse of oil, and declines of the main American indices, which are transmitted on the European market, where there are large declines in the indices, or even close the stock market. As Benoit Mandelbrot describes the phenomenon of volatility when it comes to markets: "big changes tend to be followed by big changes, and small changes tend to be followed by small changes". The phenomenon of volatility clustering (Figure 1) is observed especially when there are long periods of high market volatility or the relative rate at which the price changes a financial asset, followed by a period of calm or low volatility.

4.2 GARCH Models

4.2.1 Data series stationarity and normality analysis

With the help of the two tests, the ADF test (Augmented Dickey Fuller) and the KPSS test (Kwiatkowski - Phillips - Schmidt - Shin) we test the stationarity of the analyzed data series. The test results are presented in Table 2, and what can be seen is that the series are stationary, presenting in the case of the ADF test a probability that does not exceed the threshold of 0.05, and in the case of the KPSS test a probability above the allowed threshold. Testing the hypothesis that the data series is normally distributed was performed by applying both the Jarque-Bera test and the Kolmogorov-Smirnov test, and the results are shown in Table 3, illustrating that the null hypothesis (H_0: series comes from a normal distribution) tested is thus rejected with a $p < 0.05$.

Table 2. ADF and KPSS stationarity tests

Stationary testing for the yields of the 10 stock market indices						
	ADF			KPSS		
	H_0 null hypothesis	t-Statistic	p-value	H_0 null hypothesis	t-statistic	p-value
RFTSE100	The series has a unitary root	-9.3932	0.01	The series is stationary	0.059045	0.1
RDAX30	The series has a unitary root	-9.4051	0.01	The series is stationary	0.060373	0.1
RCAC40	The series has a unitary root	-9.511	0.01	The series is stationary	0.071423	0.1
RSMI20	The series has a unitary root	-9.6921	0.01	The series is stationary	0.040216	0.1
RAEX25	The series has a unitary root	-9.752	0.01	The series is stationary	0.099762	0.1
RPX	The series has a unitary root	-9.1316	0.01	The series is stationary	0.15212	0.1
RWIG	The series has a unitary root	-9.1458	0.01	The series is stationary	0.14441	0.1
RBET	The series has a unitary root	-8.6167	0.01	The series is stationary	0.098512	0.1
RDJI30	The series has a unitary root	-9.76	0.01	The series is stationary	0.052834	0.1
RS&P500	The series has a unitary root	-9.3556	0.01	The series is stationary	0.075881	0.1
RNASDAQ100	The series has a unitary root	-10.391	0.01	The series is stationary	0.077222	0.1

Source: Author's work

Table 3. Jarque Bera and Kolmogorov-Smirnov tests

Testing the normality of the series distribution					
Jarque-Bera Normality Test			Kolmogorov-Smirnov test		
Series	df	p-value	Series	D	p-value
European stock market indices					
RFTSE100	2	p-value < 2.2e-16	RFTSE100	0.079	1.436e-06
RDAX30	2	p-value < 2.2e-16	RDAX30	0.086	1.164e-07
RCAC40	2	p-value < 2.2e-16	RCAC40	0.096	2.098e-09
RSMI20	2	p-value < 2.2e-16	RSMI20	0.099	4.88e-10
RAEX25	2	p-value < 2.2e-16	RAEX25	0.097	1.43e-09
RPX	2	p-value < 2.2e-16	RPX	0.119	3.231e-14
RWIG	2	p-value < 2.2e-16	RWIG	0.047	0.01411
RBET	2	p-value < 2.2e-16	RBET	0.123	2.776e-15
American stock market indices					
RDJI30	2	p-value < 2.2e-16	RDJI30	0.13165	p-value < 2.2e-16
RS&P500	2	p-value < 2.2e-16	RS&P500	0.13829	p-value < 2.2e-16
RNASDAQ100	2	p-value < 2.2e-16	RNASDAQ100	0.10678	1.732e-11

Source: Author's work

4.2.2 Heteroskedasticity Breusch-Pagan-Godfrey test

To see the existence of heteroskedasticity in the data we use the Breusch-Pagan-Godfrey test and, according to the results obtained, the probability lower than the allowed threshold of 0.05 shows that the data series is heteroskedastic and can be modeled using GARCH models.

Table 4. Testing Heteroskedasticity Breusch-Pagan-Godfrey test

Series	F-statistic	Obs*R-squared	Prob. F(1,1115)	Prob. Chi-Square (1)	Prob. Chi-Square (1)
European stock market indices					
RFTSE100	99.166	91.230	0.000	0.000	0.000
RDAX30	60.380	57.381	0.000	0.000	0.000
RCAC40	110.965	101.102	0.000	0.000	0.000
RSMI20	109.862	100.187	0.000	0.000	0.000
RAEX25	107.780	98.456	0.000	0.000	0.000
RPX	46.397	44.624	0.000	0.000	0.000
RWIG	126.500	113.814	0.000	0.000	0.000
RBET	242.693	199.668	0.000	0.000	0.000
American stock market indices					
RDJI30	74.379	69.853	0.000	0.000	0.000
RS&P500	101.909	93.542	0.000	0.000	0.000
RNASDAQ100	84.927	79.058	0.000	0.000	0.000

Source: Author's work

4.2.3 Models results

Following the application of the GARCH model (1,1) on the 11 yields of the chosen stock indices, the volatility coefficients can be observed, one in front of the ARCH effect (α_1 values) and another in front of the GARCH effect (β_1 values), both coefficients being positive. their sum having values between 0 and 1, which means that the theory regarding $\alpha + \beta < 1$ is respected. In terms of statistical significance, it can be said, with a significance level of 1%, the parameters estimated in the equation of conditional variance are statistically significant, although the sum of the coefficients is subunit and the model for most indices has quite pronounced GARCH effect, but because the BET index does not show a very pronounced GARCH effect, the variance is significantly influenced by the square of the error.

Table 5. GARCH (1,1)

GARCH (1,1)				
Series	ω	α_1	β_1	$\alpha_1 + \beta_1$
RFTSE100	0.030 (0.000)	0.108 (0.000)	0.859 (0.000)	0.968
RDAX30	0.054 (0.000)	0.114 (0.000)	0.843 (0.000)	0.958
RCAC40	0.081 (0.000)	0.186 (0.000)	0.752 (0.000)	0.939
RSMI20	0.062 (0.000)	0.158 (0.000)	0.767 (0.000)	0.926
RAEX25	0.051 (0.000)	0.139 (0.000)	0.809 (0.000)	0.948
RPX	0.031 (0.000)	0.117 (0.000)	0.835 (0.000)	0.952
RWIG	0.036 (0.000)	0.061 (0.000)	0.907 (0.000)	0.969
RBET	0.143 (0.000)	0.491 (0.000)	0.493 (0.000)	0.985
RDJI30	0.053 (0.000)	0.202 (0.000)	0.750 (0.000)	0.952
RS&P500	0.057 (0.000)	0.223 (0.000)	0.725 (0.000)	0.949
RNASDAQ100	0.081 (0.000)	0.169 (0.000)	0.786 (0.000)	0.955

Source: Author's work

Analyzing the asymmetric model EGARCH (1,1), estimated by default on an ARMA model (1,1), which allows the study of the asymmetric impact of positive and negative information by including in the model the parameter γ_1, and looking at the p-values presented in the table above, it can be said that, although they are below the significance threshold, the value of the asymmetry coefficient is not negative, which means that the model does not have the asymmetry property of volatility.

Table 6. EGARCH (1,1)

EGARCH (1,1)							
	μ	AR_1	MA_1	ω	α_1	β_1	γ_1
EGARCH (1,1) RFTSE100	-0.001 (0.934)	-0.625 (0.000)	0.613 (0.000)	0.0006 (0.872)	-0.101 (0.000)	0.983 (0.000)	0.115 (0.000)
EGARCH (1,1) RDAX30	0.034 (0.081)	-0.540 (0.000)	0.537 (0.000)	0.009 (0.077)	-0.134 (0.000)	0.968 (0.000)	0.136 (0.000)

EGARCH (1,1) RCAC40	0.008 (0.768)	0.620 (0.000)	-0.555 (0.000)	0.005 (0.4361)	-0.199 (0.000)	0.952 (0.000)	0.185 (0.000)
EGARCH (1,1) RSMI20	0.018 (0.411)	-0.071 (0.297)	0.099 (0.149)	-0.016 (0.085)	-0.186 (0.000)	0.938 (0.000)	0.161 (0.003)
EGARCH (1,1) RAEX25	0.032 (0.167)	-0.611 (0.000)	0.604 (0.000)	0.0002 (0.968)	-0.154 (0.000)	0.967 (0.000)	0.144 (0.000)
EGARCH (1,1) RPX	0.024 (0.316)	0.818 (0.000)	-0.785 (0.000)	-0.009 (0.177)	-0.092 (0.000)	0.966 (0.000)	0.205 (0.000)
EGARCH (1,1) RWIG	-0.010 (0.656)	0.944 (0.000)	-0.901 (0.000)	0.004 (0.105)	-0.107 (0.000)	0.988 (0.000)	0.073 (0.000)
EGARCH (1,1) RBET	0.080 (0.000)	0.911 (0.000)	0.922 (0.000)	0.006 (0.553)	-0.154 (0.000)	0.926 (0.000)	0.341 (0.000)
EGARCH (1,1) RDJI30	0.075 (0.000)	-0.626 (0.000)	0.613 (0.000)	-0.001 (0.813)	-0.135 (0.000)	0.950 (0.000)	0.280 (0.000)
EGARCH (1,1) RS&P500	0.076 (0.000)	-0.477 (0.000)	0.396 (0.000)	-0.005 (0.580)	-0.150 (0.000)	0.925 (0.000)	0.377 (0.000)
EGARCH (1,1) RNASDAQ100	0.089 (0.000)	-0.822 (0.000)	0.7819 (0.000)	0.029 (0.000)	-0.1163 (0.000)	0.946 (0.000)	0.254 (0.000)

Source: Author's work

The persistence of volatility is visibly present with strong effects, as follows: (0.983) for the FTSE100 index, (0.968) for the DAX30 index (0.952) for the CAC40 index (0.938) for the SMI20 index, (0.967) for the AEX25 index, (0.966) for the index PX (0.988) for the WIG index, (0.926) for the BET index (0.950) for the DJI index (0.925) for the S&P500 and (0.946) for the NASDAQ100, while the ARCH effect (α_1 values) is negative. After applying the APARCH model (1,1) on the chosen data series, we can say the same as in the previous model, that it captures the asymmetry in the yield volatility, having estimates of the parameter γ_1, which captures much greater leverage than the previous model. This is visible as a result of entering the parameter δ. A positive value parameter γ_1 shows that negative information has a stronger impact than positive information on price volatility.

Table 7. APARCH (1,1)

APARCH (1,1)								
	μ	AR_1	MA_1	ω	α_1	β_1	γ_1	δ
APARCH (1,1) RFTSE100	-0.005 (0.039)	-0.617 (0.000)	0.595 (0.000)	0.019 (0.001)	0.071 (0.000)	0.931 (0.000)	0.873 (0.000)	0.777 (0.000)
APARCH (1,1) RDAX30	0.033 (0.001)	-0.618 (0.000)	0.613 (0.000)	0.043 (0.000)	0.097 (0.000)	0.896 (0.000)	0.956 (0.000)	0.800 (0.000)
APARCH (1,1) RCAC40	-0.003 (0.853)	0.620 (0.000)	-0.553 (0.000)	0.059 (0.000)	0.135 (0.000)	0.845 (0.000)	1.000 (0.000)	0.993 (0.000)
APARCH (1,1) RSMI20	0.022 (0.332)	0.037 (0.934)	0.002 (0.996)	0.070 (0.002)	0.1168 (0.000)	0.822 (0.000)	0.999 (0.000)	1.101 (0.000)
APARCH (1,1) RAEX25	0.034 (0.143)	-0.632 (0.000)	0.625 (0.000)	0.036 (0.000)	0.076 (0.000)	0.886 (0.000)	0.999 (0.000)	1.316 (0.000)
APARCH (1,1) RPX	0.024 (0.309)	0.827 (0.000)	-0.794 (0.000)	0.034 (0.000)	0.117 (0.000)	0.869 (0.000)	0.471 (0.000)	0.929 (0.004)
APARCH (1,1) RWIG	0.014 (0.661)	0.680 (0.065)	-0.645 (0.092)	0.025 (0.089)	0.025 (0.000)	0.934 (0.000)	0.999 (0.000)	1.845 (0.000)
APARCH (1,1) RBET	0.080 (0.000)	0.901 (0.000)	-0.914 (0.000)	0.082 (0.000)	0.234 (0.000)	0.745 (0.000)	0.457 (0.000)	0.944 (0.000)
APARCH (1,1) RDJI30	0.073 (0.000)	-0.646 (0.000)	0.634 (0.000)	0.052 (0.000)	0.1694 (0.0000)	0.810 (0.000)	0.525 (0.000)	1.138 (0.000)
APARCH (1,1) RS&P500	0.066 (0.000)	-0.229 (0.000)	0.142 (0.000)	0.071 (0.000)	0.1767 (0.000)	0.794 (0.000)	0.665 (0.000)	0.418 (0.008)
APARCH (1,1) RNASDAQ100	0.074 (0.000)	-0.822 (0.000)	0.7872 (0.000)	0.068 (0.000)	0.144 (0.000)	0.838 (0.000)	0.554 (0.001)	0.894 (0.001)

Source: Author's work

4.2.4 BVGARCH/BEKK

The coefficients: ω_1, ω_2, ω_3, show the asymmetric effects, namely: when the two yields of the stock indices have simultaneous negative shocks, these negative shocks must increase either the first or the second variation of the returns of the two indices in the next period. Coefficient: α_2 (cross effect) is a cross effect on the residues of the analyzed series and the coefficient β_2 represents a cross effect on volatility (cross effect) and, assuming that the two return covariances of the returns of the two indices are positive, there is an increase in the yield coefficients of the stock market indices in the next period.

Coefficients λ illustrated in table 8, show low values and, in most cases, statistically insignificant probabilities (prob > 0.05) which denotes their inability to capture the effects of shock, returns or volatility of indices. However, there are a few cases in which λ_1 and λ_2 are statistically significant, which shows a persistence of correlations and shocks, and where λ_2 it significantly shows a one-way relationship from one index to the other such as: PX→ S&P500, S&P500→ DJI30, DJI30→ S&P500, CAC40→ DJI30, PX→ DJI30, BET→ DJI30, AEX25→ NASDAQ100 and PX→ NASDAQ10. From the results obtained, it can be seen that all the α_1 coefficients have positive values, which means that, for all other indices, a shock that appeared at the first yield on the first index has a positive effect on both indices and returns the covariance in the next period. After analyzing the α_2 coefficient, we can say that, in most cases, it is statistically significant, but it has both positive and negative values, which means that a shock on the return of the second yield of the index and it also affects both positively and negatively, in some cases, the covariance of yields indices in the next period. According to the results obtained from the other indices and, based on the α_1 values, in the case of indices S&P500→ FTSE100 we can say that an increase in yield by 1 pp changes the variance of the other index. Regarding the effects of variance and covariance, a positive β_1 coefficient, as our results show, denotes the increase in the yield variance of the first index (S&P500 for example) and a positive effect on the returns of the two indices S&P500 and FTSE100. The coefficient β_2 presents both positive and negative values. The negative values are showing the decrease in both covariance and the stocks' returns in the next period. From the perspective of asymmetric effects, coefficients ω_1 shows both positive and negative values, which indicates, in the case of positive values, that there is no negative shock on the first yield of the index and, in the case of negative values, that there is a negative shock on the first yield of the index. The ω_2 coefficient presents, as in the case of the ω_1 coefficient, positive and negative values, which indicates the existence of a negative shock at the second yield of the indices: S&P500 (for S&P500→WIG, S&P500→ NASDAQ100), BET (for BET→ S&P500), NASDAQ100 (for NASDAQ100→ DJI30), PX (for PX→ NASDAQ100), WIG (for WIG→ NASDAQ100), BET (for BET→ NASDAQ100), DJI30 (for DJI30→

NASDAQ100) and the difference between the two indices increases. If the calculation $\omega(1,2) \cdot \omega(2,1) + \omega(1,1) \cdot \omega(2,2)$ results in a positive value, then the yields of the two indices are simultaneously affected by negative shocks. By using the data from the above tables, we were able to compute this equation and we've obtained, in most cases, positive values, which denote that the yields of the analyzed index pairs are simultaneously affected by negative shocks. It can also be noted that the equation outputted negative values, as in the case of: S&P500→ BET (–0.03267), S&P500→ NASDAQ100 (–0.04674), NASDAQ100→PX (–0.304), NASDAQ100→ WIG (–0.044), NASDAQ100→ BET (–0.313), NASDAQ100→ DJI30 (–0.056), NASDAQ100→ S&P500 (–0.052), which shows that the analyzed index pairs do not have simultaneous negative shocks.

Table 8. BVGARCH /BEKK

Index	α_1	α_2	α_3	β_1	β_2	β_3	ω_1	ω_2	ω_3
European stock market indices									
SP500→FTSE100	0.395625 (0.0000)	0.227975 (0.0000)	0.300756 (0.0000)	0.854782 (0.0000)	-0.058837 (0.0002)	0.938118 (0.0000)	0.244064 (0.0000)	0.183327 (0.0000)	-0.004365 (0.9960)
FTSE100→SP500	0.243587 (0.0000)	-0.040408 (0.0392)	0.469730 (0.0000)	0.945692 (0.0000)	0.036552 (0.0000)	0.861139 (0.0000)	0.130508 (0.0000)	0.169514 (0.0000)	0.163333 (0.0000)
DJI30→FTSE100	0.374910 (0.0000)	0.235308 (0.0000)	0.289281 (0.0000)	0.859603 (0.0000)	-0.032709 (0.0524)	0.944888 (0.0000)	0.219901 (0.0000)	0.124552 (0.0005)	0.109495 (0.0000)
FTSE100→DJI30	0.236074 (0.0000)	-0.044473 (0.0129)	0.439910 (0.0000)	0.940978 (0.0000)	0.042285 (0.0000)	0.881384 (0.0000)	0.140393 (0.0000)	0.118884 (0.0005)	0.179281 (0.0000)
NASDAQ100→ FTSE100	0.389603 (0.0000)	0.230353 (0.0000)	0.289923 (0.0000)	0.876695 (0.0000)	-0.089097 (0.0000)	0.940592 (0.0000)	0.330782 (0.0000)	0.182704 (0.0000)	0.029591 (0.7866)
FTSE100→ NASDAQ100	0.250691 (0.0000)	-0.072669 (0.0000)	0.401836 (0.0000)	0.949837 (0.0000)	0.037805 (0.0000)	0.892211 (0.0000)	0.092104 (0.0001)	0.126917 (0.0540)	0.266086 (0.0000)
S&P500→DAX30	0.467201 (0.0000)	0.039434 (0.1289)	0.252474 (0.0000)	0.848724 (0.0000)	0.007384 (0.5655)	0.953457 (0.0000)	0.234577 (0.0000)	0.156352 (0.0000)	0.115431 (0.0010)
DAX30→ S&P500	0.276556 (0.0000)	-0.132431 (0.0000)	0.440758 (0.0000)	0.902949 (0.0000)	0.092698 (0.0000)	0.881733 (0.0000)	0.218185 (0.0000)	0.118656 (0.0000)	0.179556 (0.0000)
DJI30→DAX30	0.387936 (0.0000)	0.155571 (0.0000)	0.267568 (0.0000)	0.856371 (0.0000)	-0.007208 (0.6205)	0.948536 (0.0000)	0.225138 (0.0000)	0.144646 (0.0003)	0.142635 (0.0000)
DAX30→DJI30	0.244898 (0.0000)	-0.145419 (0.0000)	0.428988 (0.0000)	0.847784 (0.0000)	0.158297 (0.0000)	0.887961 (0.0000)	0.295637 (0.0000)	0.044932 (0.0362)	0.205914 (0.0000)
NASDAQ100→ DAX30	0.405503 (0.0000)	0.095285 (0.0024)	0.248163 (0.0000)	0.882454 (0.0000)	-0.024985 (0.0583)	0.954918 (0.0000)	0.310553 (0.0000)	0.164557 (0.0000)	0.100647 (0.0051)
DAX30→ NASDAQ100	0.246720 (0.0000)	-0.093692 (0.0000)	0.396135 (0.0000)	0.943258 (0.0000)	0.045954 (0.0000)	0.898120 (0.0000)	0.138723 (0.0000)	0.166464 (0.0024)	0.228993 (0.0000)
SP500→CAC40	0.420224 (0.0000)	0.110366 (0.0000)	0.314896 (0.0000)	0.878455 (0.0000)	-0.046215 (0.0018)	0.924528 (0.0000)	0.241718 (0.0000)	0.235812 (0.0000)	0.068745 (0.2621)
CAC40→ SP500	0.307917 (0.0000)	-0.081511 (0.0003)	0.439935 (0.0000)	0.928077 (0.0000)	0.034017 (0.0002)	0.879123 (0.0000)	0.196825 (0.0000)	0.167774 (0.0000)	0.145708 (0.0000)
DJI30→CAC40	0.387316 (0.0000)	0.145445 (0.0000)	0.326875 (0.0000)	0.886265 (0.0000)	-0.053356 (0.0008)	0.917418 (0.0000)	0.238486 (0.0000)	0.239773 (0.0000)	0.098118 (0.0338)
CAC40→DJI30	0.270740 (0.0000)	-0.109173 (0.0004)	0.490105 (0.0000)	0.854261 (0.0000)	0.141071 (0.0000)	0.849411 (0.0000)	0.259289 (0.0000)	0.083874 (0.0019)	0.240129 (0.0000)
NASDAQ100→ CAC40	0.393481 (0.0000)	0.093710 (0.0019)	0.296724 (0.0000)	0.898584 (0.0000)	-0.045541 (0.0030)	0.933744 (0.0000)	0.295708 (0.0000)	0.182916 (0.0000)	0.133321 (0.0000)
CAC40→ NASDAQ100	0.303804 (0.0000)	-0.097241 (0.0000)	0.379524 (0.0000)	0.932082 (0.0000)	0.034172 (0.0000)	0.906642 (0.0000)	0.172857 (0.0000)	0.148804 (0.0000)	0.225819 (0.0000)
SP500→SMI20	0.441341 (0.0000)	0.131463 (0.0001)	0.316338 (0.0000)	0.863736 (0.0000)	-0.059510 (0.0084)	0.914854 (0.0000)	0.257204 (0.0000)	0.209057 (0.0000)	0.108228 (0.0231)
SMI20→ SP500	0.296898 (0.0000)	-0.097914 (0.0000)	0.447360 (0.0000)	0.895848 (0.0000)	0.060560 (0.0000)	0.873760 (0.0000)	0.224725 (0.0000)	0.111538 (0.0000)	0.199645 (0.0000)
DJI30→SMI20	0.430252 (0.0000)	0.065420 (0.0648)	0.310912 (0.0000)	0.891070 (0.0000)	-0.041026 (0.0453)	0.916249 (0.0000)	0.223486 (0.0000)	0.200844 (0.0000)	0.124314 (0.0013)
SMI20→DJI30	0.312229 (0.0000)	-0.096334 (0.0000)	0.410605 (0.0000)	0.900099 (0.0000)	0.045223 (0.0000)	0.900847 (0.0000)	0.230157 (0.0000)	0.103626 (0.0000)	0.159755 (0.0000)
NASDAQ100→ SMI20	0.411736 (0.0000)	0.167993 (0.0000)	0.300537 (0.0000)	0.879536 (0.0000)	-0.092479 (0.0006)	0.919156 (0.0000)	0.344570 (0.0000)	0.210723 (0.0000)	0.107995 (0.0210)
SMI20→ NASDAQ100	0.304943 (0.0000)	-0.121871 (0.0000)	0.395373 (0.0000)	0.897014 (0.0000)	0.054655 (0.0000)	0.894561 (0.0000)	0.208375 (0.0000)	0.118414 (0.0011)	0.274568 (0.0000)
SP500→AEX25	0.445318 (0.0000)	0.058109 (0.0393)	0.259127 (0.0000)	0.863859 (0.0000)	-0.012379 (0.4469)	0.947176 (0.0000)	0.242183 (0.0000)	0.171280 (0.0000)	0.082577 (0.0555)
AEX25→ SP500	0.289887 (0.0000)	-0.112824 (0.0000)	0.415403 (0.0000)	0.916866 (0.0000)	0.058074 (0.0000)	0.891311 (0.0000)	0.181289 (0.0000)	0.141250 (0.0000)	0.159725 (0.0000)
DJI30→AEX25	0.392214 (0.0000)	0.136586 (0.0000)	0.265969 (0.0000)	0.878153 (0.0000)	-0.032712 (0.0367)	0.944132 (0.0000)	0.234884 (0.0000)	0.181377 (0.0000)	0.075191 (0.1316)
AEX25→DJI30	0.279913 (0.0000)	-0.118484 (0.0000)	0.404925 (0.0000)	0.906497 (0.0000)	0.070041 (0.0000)	0.900080 (0.0000)	0.196664 (0.0000)	0.102173 (0.0000)	0.171688 (0.0000)
NASDAQ100→ AEX25	0.398001 (0.0000)	0.139819 (0.0001)	0.253857 (0.0000)	0.881265 (0.0000)	-0.045056 (0.0133)	0.948853 (0.0000)	0.325452 (0.0000)	0.172188 (0.0000)	0.080336 (0.0552)
AEX25→ NASDAQ100	-0.194529 (0.0000)	0.319154 (0.0000)	0.463117 (0.0000)	0.933514 (0.0000)	-0.102231 (0.0000)	0.861461 (0.0000)	0.304793 (0.0000)	0.291761 (0.0000)	-0.160599 (0.0000)

SP500→PX	0.509878 (0.0000)	0.102701 (0.0015)	0.294186 (0.0000)	0.797853 (0.0000)	0.015223 (0.4664)	0.940788 (0.0000)	0.288529 (0.0000)	0.024227 (0.3915)	0.142791 (0.0000)
PX→ SP500	0.264027 (0.0000)	-0.014562 (0.4796)	0.558800 (0.0000)	0.912763 (0.0000)	0.053296 (0.0001)	0.793488 (0.0000)	0.178162 (0.0000)	0.030572 (0.2886)	0.297978 (0.0000)
DJI30→PX	0.517073 (0.0000)	0.094596 (0.0052)	0.298874 (0.0000)	0.796068 (0.0000)	0.024779 (0.2545)	0.939171 (0.0000)	0.289820 (0.0000)	0.017865 (0.5348)	0.143757 (0.0000)
PX→DJI30	0.277096 (0.0000)	-0.041360 (0.0426)	0.541451 (0.0000)	0.901920 (0.0000)	0.066253 (0.0000)	0.811266 (0.0000)	0.180184 (0.0000)	0.024807 (0.4112)	0.285087 (0.0000)
NASDAQ100→ PX	0.411789 (0.0000)	0.154778 (0.0004)	0.290170 (0.0000)	0.879120 (0.0000)	-0.050220 (0.0136)	0.940189 (0.0000)	0.305460 (0.0000)	0.073630 (0.0024)	0.131512 (0.0000)
PX→ NASDAQ100	-0.190255 (0.0000)	0.238927 (0.0000)	0.522795 (0.0000)	0.935167 (0.0000)	-0.106443 (0.0000)	0.824043 (0.0000)	-0.196948 (0.0000)	-0.304242 (0.0000)	0.226522 (0.0000)
S&P500→WIG	0.530071 (0.0000)	-0.054426 (0.0146)	0.226797 (0.0000)	0.814701 (0.0000)	0.056139 (0.0005)	0.959257 (0.0000)	0.227438 (0.0000)	-0.012516 (0.8154)	0.191958 (0.0000)
WIG→ S&P500	0.221669 (0.0000)	0.012297 (0.6275)	0.512691 (0.0000)	0.947629 (0.0000)	0.015806 (0.2783)	0.836478 (0.0000)	0.220153 (0.0000)	0.143089 (0.0000)	0.205391 (0.0000)
DJI30→WIG	0.501376 (0.0000)	0.000478 (0.9845)	0.237453 (0.0000)	0.824408 (0.0000)	0.032930 (0.0448)	0.955294 (0.0000)	0.248886 (0.0000)	0.050951 (0.2748)	0.195004 (0.0000)
WIG→DJI30	0.233030 (0.0000)	-0.024918 (0.3010)	0.484454 (0.0000)	0.932935 (0.0000)	0.040537 (0.0055)	0.851868 (0.0000)	0.238648 (0.0000)	0.109389 (0.0004)	0.219741 (0.0000)
NASDAQ100→ WIG	0.422343 (0.0000)	-0.004702 (0.8514)	0.213449 (0.0000)	0.884239 (0.0000)	0.006988 (0.5893)	0.962268 (0.0000)	0.289119 (0.0000)	0.096130 (0.0096)	0.164815 (0.0000)
WIG→ NASDAQ100	0.223741 (0.0000)	-0.031390 (0.0858)	0.406698 (0.0000)	0.955984 (0.0000)	0.013044 (0.1587)	0.891531 (0.0000)	-0.194263 (0.0000)	-0.155652 (0.0002)	0.242718 (0.0000)
S&P500 → BET	0.508389 (0.0000)	0.080375 (0.0177)	0.364292 (0.0000)	0.825301 (0.0000)	-0.007693 (0.6343)	0.910251 (0.0000)	0.266190 (0.0000)	0.048741 (0.2095)	0.242602 (0.0000)
BET →S&P500	0.220217 (0.0000)	-0.128646 (0.0000)	0.557624 (0.0000)	0.868893 (0.0000)	0.185177 (0.0000)	0.795996 (0.0000)	0.241742 (0.0000)	-0.121285 (0.0000)	0.275804 (0.0000)
DJI30 →BET	0.488336 (0.0000)	0.120603 (0.0005)	0.389272 (0.0000)	0.829003 (0.0000)	-0.018515 (0.3020)	0.903978 (0.0000)	0.271882 (0.0000)	0.040447 (0.2753)	0.240385 (0.0000)
BET→DJI30	0.216296 (0.0000)	0.241856 (0.0000)	0.564395 (0.0000)	0.936721 (0.0000)	-0.150061 (0.0000)	0.803746 (0.0000)	0.213337 (0.0000)	0.194551 (0.0000)	0.210377 (0.0000)
NASDAQ100 → BET	0.320720 (0.0000)	0.315735 (0.0000)	0.796258 (0.0000)	0.929489 (0.0000)	-0.135325 (0.0008)	0.554176 (0.0000)	0.182771 (0.0000)	0.149314 (0.0746)	0.499477 (0.0000)
BET → NASDAQ100	0.256697 (0.0000)	-0.158872 (0.0000)	0.470249 (0.0000)	0.889234 (0.0000)	0.135531 (0.0000)	0.846863 (0.0000)	0.152131 (0.0003)	-0.313162 (0.0001)	0.205134 (0.0452)
American stock market indices									
SP500→DJI30	0.202502 (0.0000)	0.317209 (0.0000)	0.530721 (0.0000)	0.971966 (0.0000)	-0.151596 (0.0000)	0.819566 (0.0000)	0.258232 (0.0000)	0.268927 (0.0000)	0.031346 (0.0000)
DJI30→ SP500	0.186471 (0.0000)	0.360088 (0.0000)	0.534853 (0.0000)	0.978193 (0.0000)	-0.158512 (0.0000)	0.820850 (0.0000)	0.238596 (0.0000)	0.256658 (0.0000)	0.020484 (0.0309)
SP500→ NASDAQ100	0.319461 (0.0000)	0.118680 (0.0000)	0.409799 (0.0000)	0.911065 (0.0000)	-0.035802 (0.0001)	0.899769 (0.0000)	-0.214819 (0.0000)	-0.237220 (0.0000)	0.084189 (0.0000)
NASDAQ100→ SP500	0.271848 (0.0000)	0.209077 (0.0000)	0.502907 (0.0000)	0.942610 (0.0000)	-0.076098 (0.0000)	0.843414 (0.0000)	0.271224 (0.0000)	0.232545 (0.0000)	0.070016 (0.0000)
NASDAQ100→ DJI30	0.266221 (0.0000)	0.193757 (0.0000)	0.495326 (0.0000)	0.955239 (0.0000)	-0.088211 (0.0000)	0.842123 (0.0000)	0.254200 (0.0000)	0.234832 (0.0000)	0.102325 (0.0000)
DJI30→ NASDAQ100	0.295751 (0.0000)	0.146103 (0.0000)	0.401768 (0.0000)	0.929454 (0.0000)	-0.055928 (0.0000)	0.901516 (0.0000)	-0.206211 (0.0000)	-0.233198 (0.0000)	0.096952 (0.0000)

Table 8 continued

Index	λ_1	λ_2	μ_1	μ_2	Index	λ_1	λ_2	μ_1	μ_2
European stock market indices					European stock market indices				
SP500→ FTSE100	0.043518 (0.0526)	0.036528 (0.2912)	0.102704 (0.0000)	0.041400 (0.2315)	AEX25→ DJI30	0.014670 (0.6391)	0.013034 (0.6199)	0.054944 (0.1331)	0.089804 (0.0010)
FTSE100→ SP500	0.021595 (0.5748)	0.035568 (0.1518)	0.015838 (0.6645)	0.089852 (0.0002)	NASDAQ100 → AEX25	0.025134 (0.3457)	0.007458 (0.7894)	0.125928 (0.0012)	0.071046 (0.0441)
DJI30→ FTSE100	0.039488 (0.0888)	0.040014 (0.2516)	0.091153 (0.0002)	0.032647 (0.3416)	AEX25→ NASDAQ100	0.004281 (0.8654)	0.070413 (0.0003)	0.060316 (0.0838)	0.093899 (0.0098)
FTSE100→ DJI30	0.021084 (0.5801)	0.026815 (0.2836)	0.015398 (0.6828)	0.085258 (0.0013)	SP500→PX	0.073496 (0.0023)	0.063158 (0.0877)	0.069077 (0.0043)	0.028269 (0.2921)
NASDAQ10→ FTSE100	0.030738 (0.2040)	0.008778 (0.7742)	0.131371 (0.0011)	0.038776 (0.2639)	PX→ SP500	0.036218 (0.3673)	0.075226 (0.0011)	0.028443 (0.3332)	0.068442 (0.0059)
FTSE100→ NASDAQ100	-0.005765 (0.8621)	0.028999 (0.2353)	0.022071 (0.5343)	0.110917 (0.0048)	DJI30→PX	0.056907 (0.0204)	0.055868 (0.1301)	0.070649 (0.0065)	0.029593 (0.2705)
S&P500→ DAX30	0.050105 (0.0491)	0.040339 (0.1703)	0.089898 (0.0001)	0.049052 (0.2267)	PX→DJI30	0.023473 (0.5425)	0.054899 (0.0131)	0.035169 (0.2279)	0.072012 (0.0065)
DAX30→ S&P500	0.028694 (0.3429)	0.037097 (0.1770)	0.042399 (0.3130)	0.086043 (0.0003)	NASDAQ100 → PX	0.037783 (0.1416)	0.031245 (0.4313)	0.093168 (0.0169)	0.033729 (0.2151)
DJI30→ DAX30	0.039467 (0.1079)	0.031920 (0.2736)	0.100259 (0.0001)	0.071269 (0.0779)	PX→ NASDAQ100	-0.043200 (0.1184)	0.052330 (0.0005)	0.063074 (0.0182)	0.104818 (0.0026)
DAX30→ DJI30	0.030263 (0.3121)	0.033147 (0.1836)	0.034955 (0.4236)	0.083770 (0.0016)	S&P500→WI G	0.030087 (0.1202)	0.067524 (0.1311)	0.093064 (0.0000)	-0.013074 (0.8209)
NASDAQ100→D AX30	0.029734 (0.2493)	0.010212 (0.7019)	0.125588 (0.0008)	0.068067 (0.0868)	WIG→ S&P500	0.062996 (0.1877)	0.028133 (0.1611)	-0.001248 (0.9833)	0.097787 (0.0000)
DAX30→ NASDAQ100	0.003989 (0.8809)	0.021817 (0.4006)	0.058656 (0.1521)	0.121810 (0.0017)	DJI30→WIG	0.024259 (0.1992)	0.065094 (0.1432)	0.090945 (0.0003)	-0.000887 (0.9878)
SP500→ CAC40	0.050621 (0.0427)	0.033197 (0.1284)	0.096363 (0.0000)	0.067186 (0.0532)	WIG→DJI30	0.057277 (0.2466)	0.021390 (0.2720)	0.003558 (0.9542)	0.090547 (0.0004)
CAC40→ SP500	0.027641 (0.2297)	0.038874 (0.1602)	0.048170 (0.1716)	0.083055 (0.0005)	NASDAQ100 →WIG	0.029888 (0.2133)	0.057214 (0.1884)	0.112496 (0.0039)	-0.013063 (0.8149)
DJI30→ CAC40	0.040921 (0.0876)	0.030913 (0.1434)	0.095616 (0.0002)	0.066542 (0.0558)	WIG→ NASDAQ100	0.053171 (0.2237)	0.027781 (0.2382)	-0.009314 (0.8706)	0.111941 (0.0042)

CAC40→ DJI30	0.027300 (0.1520)	0.044455 (0.0280)	0.046075 (0.1862)	0.081345 (0.0012)	S&P500 → BET	0.027332 (0.2131)	0.007942 (0.6464)	0.094869 (0.0000)	0.132009 (0.0000)
NASDAQ100→CAC40	0.031724 (0.2332)	0.005402 (0.8002)	0.120010 (0.0022)	0.072141 (0.0433)	BET →S&P500	0.018940 (0.1326)	0.039149 (0.0828)	0.090684 (0.0024)	0.100860 (0.0001)
CAC40→ NASDAQ100	0.000768 (0.9714)	0.026256 (0.3074)	0.062550 (0.0811)	0.107550 (0.0070)	DJI30 →BET	0.023719 (0.2347)	0.007471 (0.6353)	0.087385 (0.0007)	0.136759 (0.0000)
SP500→SMI20	0.040297 (0.0939)	0.058042 (0.0662)	0.099655 (0.0000)	0.047424 (0.1306)	BET→DJI30	0.022946 (0.1620)	0.055038 (0.0017)	0.088023 (0.0034)	0.093881 (0.0003)
SMI20→ SP500	0.036362 (0.2465)	0.030639 (0.2125)	0.041503 (0.2094)	0.088283 (0.0003)	NASDAQ100 → BET	0.060304 (0.0045)	0.025245 (0.1174)	0.083162 (0.0221)	0.120709 (0.0000)
DJI30→SMI20	0.031771 (0.1947)	0.053932 (0.0885)	0.088540 (0.0004)	0.038837 (0.2284)	BET → NASDAQ100	0.010321 (0.4117)	0.032181 (0.1427)	0.095788 (0.0006)	0.094388 (0.0195)
SMI20→DJI30	0.032440 (0.2922)	0.023165 (0.3495)	0.041201 (0.2214)	0.083078 (0.0014)	American stock market indices				
NASDAQ100→SMI20	0.033387 (0.1812)	0.036331 (0.1879)	0.119065 (0.0021)	0.048102 (0.1151)	SP500→DJI30	0.047746 (0.0057)	0.043921 (0.0110)	0.092643 (0.0000)	0.094377 (0.0000)
SMI20→ NASDAQ100	0.014035 (0.6065)	0.030053 (0.1862)	0.048553 (0.1313)	0.095825 (0.0123)	DJI30→ SP500	0.043674 (0.0079)	0.047581 (0.0039)	0.100652 (0.0000)	0.102682 (0.0000)
SP500→ AEX25	0.042222 (0.1003)	0.040188 (0.2113)	0.094787 (0.0001)	0.055047 (0.1260)	SP500→ NASDAQ100	0.001505 (0.9227)	0.007755 (0.6885)	0.126261 (0.0000)	0.177786 (0.0000
AEX25→ SP500	0.025968 (0.4208)	0.026958 (0.3079)	0.049855 (0.1654)	0.089544 (0.0002)	NASDAQ100 → SP500	0.010110 (0.6138)	0.002419 (0.8796)	0.177064 (0.0000)	0.132746 (0.0000)
DJI30→ AEX25	0.025289 (0.3061)	0.026818 (0.3777)	0.100931 (0.0001)	0.068957 (0.0591)	NASDAQ100 →DJI30	0.033384 (0.1212)	0.017046 (0.3152)	0.136414 (0.0000)	0.104682 (0.0000)
					DJI30→ NASDAQ100	0.013904 (0.3631)	0.027952 (0.1566)	0.102669 (0.0000)	0.151103 (0.0000)

Source: Author's work

The Figure 2 below shows the variance-covariance, and the influence form a market to another market.

Figure 2. Variance-Covariance (BEKK Results)
Source: Author's work

5. Contagion (spillover effect)

Contagion, at the level of financial markets, would be defined as a phenomenon that can occur as a result of instability or financial shock, but also the way it is transmitted, i.e. quickly in the situation where there are relations and interdependence between countries, or slower if relationships are weaker. Stock indices of European countries such as: Great Britain (FTSE100), Switzerland (SMI), Netherlands (AEX25), Germany (DAX), France (CAC40), Czech Republic (PX), Poland (WIG) and Romania (BET), which are the main indices of their respective country and, from an economic point of view, there are old, interconnected relations between those countries, especially that they are members of the European Union, (except Great Britain) and their interests converge towards the same ideals. As presented by Tudorache and Nicolescu (2022), the effect of the contagion has been visible in international trade relations since the beginning of the COVID-19 pandemic. What stands out is that when there are negative events that cause shocks in one market, they are transmitted very quickly, almost simultaneously in other markets, causing a chain reaction. Thus, a shock that's strong enough in one market causes damage to the securities markets and spreads them to other markets. The closing of the global economy caused by the coronavirus pandemic led to panic at the end of 2020. This is seen when, after a few severe daily declines due to the coronavirus pandemic that affected oil demand, implicitly lowering the price, the S&P500, DJI30 and Nasdaq100 indices had massive declines, followed by the analyzed European indices. Negative events occur with the onset of the coronavirus pandemic and its visible effects from an economic and social point of view, which quickly became visible on the stock market. The contagion effect is due to the independence of financial markets and the interconnection of open economies. The spread of the stock market crisis captured in the paper at the beginning of the coronavirus pandemic had negative effects on the global economy and, implicitly, on the economies of the analyzed countries.

6. Conclusions

The paper uses data sets with daily observations (5 days a week) between 7 November 2016 – 3 November 2021 based on the closing prices of the stock indices: USA (S&P500, DJI30, NQ100), United Kingdom (FTSE100), Switzerland (SMI), Netherlands (AEX25), Germany (DAX), France (CAC40), Czech Republic (PX), Poland (WIG) and Romania (BET). Using various statistical and econometric tests using the R and Eviews10 models, as well as using the GARCH family models, we observe and show the contagion of the financial markets, better illustrated at the beginning of the coronavirus pandemic, when the propagation effect is observable from the North American financial market to European stock exchanges. By applying the Jarque-Bera and Kolmogorov-Smirnov, Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) normality tests, the bivariate Breusch-Pagan, GARCH and GARCH tests are investigated, the impact of the contagion on the analyzed stock exchanges is investigated. Indices, their analysis and their movements offer a perspective on the economy in the analyzed period and the relations between them can be essential for the decisions of the investors who aim to have a diversified portfolio. Thus, it is observed on the stock exchange that the American stock indices, such as S&P500, Dow Jones and Nasdaq have a special, close relationship with the stock indices from European countries, as they are a force for leading indices in many other countries and, as the famous saying: "when Wall Street sneezes, the rest of the world catches a cold ". The interaction of the stock markets, illustrated by the transmission of shocks, shows the importance of their spread within the asset classes, but especially on the stock markets. The strongest international transmission of shocks occurs in assets, when market margins are statistically and economically significant and the direct transmission of financial shocks within asset classes is amplified, especially by spillovers, by the indirect effects of prices of other assets. From the results obtained by following the application of the BEKK model, several cases of unidirectional and bidirectional causal links emerged in terms of yields, such as: PX→S&P500, S&P500→ DJI30, DJI30→ S&P500, CAC40→ DJI30, PX→DJI30, BET→ DJI30, AEX25→NASDAQ100 and PX → NASDAQ10 and we can say, in the case of unidirectional connections, such as: PX→S&P500, CAC40→ DJI30, BET→ DJI30, AEX25→NASDAQ100 and PX→NASDAQ10, that it reflects a one-way relationship between turbulent markets due to the onset of the COVID-19 pandemic. What is observed is excessive volatility in major stock markets, with a short persistence of volatility in the first wave of the coronavirus epidemic, which is illustrated in March 2020. According to public information, the influence of the US market over the EU market is more robust than the influence of the EU market over the US market. It is noted that the US stock markets are of particular importance in reflecting the stock price movements, which triggers a corresponding change in European markets. The development of the US market through the S&P500, Nasdaq and Dow Jones indicators is also reflected in the European market.

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