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The Econometric Analysis of Volatility Dynamics between Developed Market Economies and Emerging Market Economies

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Abstract: In this study volatility dynamics between the stock markets of developed market economies and emerging market economies were analyzed. Within this context, in this study covering the period of 05.01.2000-13.01.2014, daily closing values of the stock market index of 10 countries were used, and volatility dynamics between countries were examined by using the analyses of BEKK GARCH and CCC GARCH. NSYE Composite Index (USA), FTSE 100 (UK), DAX 30 (Germany), CAC 40 (France), Nikkei 225 (Japan), IBOVESPA (Brazil), SSE Composite Index (China), HSI Index (Hong Kong), RTSI Index (Russia), BIST 100 (Istanbul) are the stock index included in the analysis. According to the findings, while there is a strong volatility spillover among developed country markets there is a weak volatility spillover, when it comes to from developed countries towards developing countries. However, domestic shocks in the previous period and the volatility of the previous period affect current period of volatility.

Keywords: Volatility Spillover, Multivariable GARCH Model

INTRODUCTION

The financial liberalization process that began in the 1980s and information and technology revolution in the 1990s have led to the acceleration of global information flow and have increased the volatility spillover between countries by speeding up the process of financial integration. Failure of the U.S. Stock Exchange in November 1987 and of the European currency mechanism in 1992 caused a number of empirical studies to be made explaining shocks spillover mechanism; Southeast Asian crisis, which occured in the 1990s increased activities related to the financial contagion [1]. While the financial contagion was perceived as a specific problem of the developing countries until 2008 Global Financial Crisis, after the 2008 Global Crisis strong findings have been reached pointing out the fact that the financial contagion is not only limited to developing countries and it is also a matter concerning the financial system in a global basis [2]. It has been once again proven that shortcomings in the financial architecture and in the financial innovation in which legal and institutional processes creating the financial system spread to every field has a structure that increases the fragility rather than ensuring the effectiveness of the market.

Volatility spillover process affects the flows of financial assets between countries and has led to significant changes in the returns of the stock market in the country, in the volume of transactions and in the market value. In 2007, the local companies being a member of WFE have a total of 61 trillion dollar market value and a volume of 99 trillion dollar stock, while at the end of 2008 depending on the global crisis, the market value has decreased to 33 trillion dollars and trading volume increased at 13% over the previous year and rose to 112 trillion $ [3-4]. In 2009 the fact that Fed explained stress tests used by financial institutions to assess capital adequacy come out positive created an air of optimism in the markets and it increased the statement of confidence in the market. Due to the increasing confidence in the markets, total market value in 2009 increased to 47 trillion dollars, but trading volume decreased by 28% compared to the previous year and decreased to 80 trillion dollars. In 2010, the market value rose to $ 55 trillion, and the transaction volume decreased by 22% to 63 trillion dollars [5-6].At the end of the 2011 because the financial crisis deepened and was transformed into a debt crisis, the total market value declined by 14% and there has been no change in the total volume of transactions while returning to the level of 2009 again. Under the influence of the expansionary monetary and fiscal policies, stock markets entered into a recovery tendency and in 2012, the total market value of local companies being a member of WFE reached to approximately 55 trillion dollars while the trading volume reached to 49 million dollars [7].

In this study volatility dynamics between the stock market of developed countries' economies and emerging market economies were analyzed. Within this context, in this study covering the period of 05.01.2000-13.01.2014, daily closing values of the stock market index of 10 countries were used and volatility dynamics between countries were examined by using the analyses of BEKK GARCH and CCC GARCH. NSYE Composite Index (USA), FTSE 100 (UK), DAX 30 (Germany), CAC 40 (France), Nikkei 225 (Japan), IBOVESPA (Brazil), SSE Composite Index (China), HSI index (Hong Kong), RTSI Index (Russia), BIST 100 (Istanbul) are the stock index included in the analysis.

RESEARCH METHODOLOGY

Financial time series have its own unique characteristics in common. Firstly financial time series are leptokurtic series. Secondly the series are stationary in its own cluster and series that followed the same trend in the stationary period series show extreme volatility in periods of crisis and they return to its former course after the crisis period. In this case, the error term gets smaller in the stationary periods, and gets larger values in the periods of fluctuations thus leading to different variance cases. Therefore primarily descriptive statistics' values belonging to index series will be examined.

Table 1: Descriptive Statistics of Return Series

	NSYE Composite Index	DAX 30	IBOVESPA	SSE Composite	CAC 40	HSI Index	FTSE 100 Index	Nıkkei 225	RTSI Index	BIST 100
Mean	0.000139	0.000119	0.000347	0.000111	-7.84E5	0.000113	1.04E-05	-4.78E-0	0.000643	0.000434
Median	0.000462	0.000734	0.000442	0.00000	0.00012	0.00000	0.000102	0.00000	0.000950	0.000837
Maksimum	0.348930	0.10685	0.125982	0.094008	0.09616	0.134068	0.286400	0.269046	0.276137	0.470279
Minimum	-0.33961	-0.09575	-0.12226	-0.09256	-0.0947	-0.13582	- 0.2695	-0.27559	-0.21199	-0.20332
SD	0.016334	0.01639	0.019470	0.016523	0.01574	0.016354	0.015278	0.019455	0.023915	0.026294
Skewness	-0.09774	-0.08472	-0.05139	0.044092	-0.0327	-0.04750	0.412815	-0.01369	-0.04110	1.548531
Kurtosis	132.9656	6.930973	7.488280	7.421075	7.13948	11.22727	78.61919	52.94510	16.32845	40.12210
Jarque Bera	2254258 (0.0000)	2066.104 (0.0000)	2689.882 (0.0000)	2609.602 (0.0000)	2287.425 (0.0000)	9034.724 (0.0000)	762340 (0.0000)	332913.7 (0.0000)	23709.45 (0.0000)	185192.4 (0.0000)

Analyzing the Table 1 it is observed that series of country returns did not have a normal distribution. While the UK stock market has the highest average return, France stock has the lowest average returns. However, Turkey is a country with the highest volatility of the stock market. Turkey is followed by the Russian stock market.

Fig-1 shows the volatility clustering in the country stock market. Analysing the table it is seen that volatility movements usually follow each other; that is to say, high fluctations follow high volatility, while low volatility tracks a low volatility.

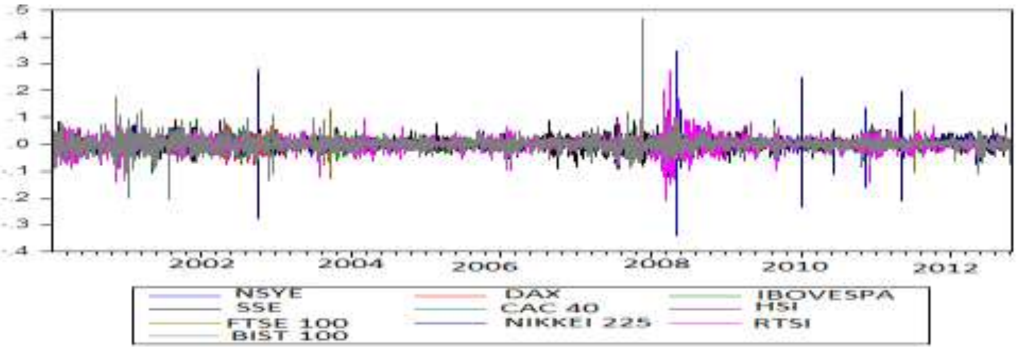

Fig-1: Volatility Clustering

In the case of a heteroscedasticity problem in the traditional time series analysis, The Least Squares estimator protect the characteristcs of unbiasedness and consistency, whereas it loses the predictive efficacy and parameters become statistically insignificant. Therefore, in the studies carried out with financial time series the nonlinear models of the conditional variance are necessary to be used rather than models of linear time series.

Models in which the long-term variance is constant, but the value of variance changes during periods of fluctuations are referred to as conditional different variance models. The different variance model (Autoregressive Conditional Heteroskedastic, ARCH) developed for the first time by Engle [8] is a model allowing the estimation of series variance and also allowing conditional variance to change over time, but accept the unconditional variance as constant. However in the ARCH (p) model the problem of over-

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parameterization is faced with. To solve this problem, Bollerslev [9] created the GARCH (p, q) model by representing the conditional variance ARMA (Autoregressive Moving Average) process. Models developed by Engle [82] and Bollerslev are univariate models [9]. The generalized form of different variance models for series of n is the VECH GARCH model developed by Bollerslev Engle and Wooldridge [10]. Due to the fact that number of parameters to be estimated is quite high in the the GARCH model and the positive certainty of the conditional variance is not guaranteed, BEKK GARCH model were developed by Engle and Kroner [11]. In this model certainty of positive variance is ensured. However Bollerslev [12] has developed a new model called the CCC GARCH which models volatility spillover process by using correlation coefficient in the conditional variance-covariance equation. In this study, to analyze the spillover of volatility between countries the models of Diagonal BEKK and CCC GARCH were used.

BEKK GARCH MODEL

The first multivariate GARCH model is the VECH GARCH model developed by Bollerslev and others [10]. In this model the conditional variance and covariance, lagged conditional variance and covariance values are considered in this case as a function of the lagged error term of the squared values and the lagged error term of the squares of the cross product and this leads over-parameterization problems in the model to be encountered. Therefore the BEKK GARCH model was developed by Engle and Kroner [11]. In the BEKK GARCH model proposed by Engle and Kroner the process begins by obtaining returns equations. Return series are defined as;

$$r_t = \alpha + \Gamma r_{t-1} + \varepsilon_t$$
$$\varepsilon_t \mid \mathrm{I}_{t-1} \approx N(0, \mathrm{H}_t)$$

As it can be seen from the Equation the return series is the sum of the error term with its delay value. Random variable of ε_t connected to prior knowledge (I_{t-1}) is zero and it variance is H_t . Selecting H_t parameter as a function of prior knowledge allows all parts of H_t to be modelled depending on the lagged values (q) of ε_t square and the cross and H_t s own lagged values (p) and weakly on the external x_t variables on jx1 vector. Therefore the elements of the covariance matrix is a vector defined by ARMAX process comprising of and the cross product of residues and the squares.

For the first time with the concept of ARCH it was used by Engle, Granger, Kraft [13] and with the concept of the diagonal presentation GARCH connecting each element of covariance matrix with $h_{jk,t}$, its own past values and $\varepsilon_{j,t}\varepsilon_{k,t}$ past values was used for the first time by Bollerslev, Engle and Woodridge [10]. That is to say the variance depends on only covariance of the squares of the residual values of its past history and covariance depends on the past values of the cross product. Because of the information that the variance is usually explained by the residual of the square that appears intuitively reasonable and if covariance changes slowly, future variance can be estimated by using delayed residual frames. A similar argument can be made for covariance. In the VECH GARCH model a diagonal presentation can be obtained assuming that matrix of A_i and G_i are diagonal. In the model, the conditional variance and covariance equations are defined as follows.

$$h_t = \begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{bmatrix} = \begin{bmatrix} c_{01} \\ c_{02} \\ c_{03} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} g_{11} & 0 & 0 \\ 0 & g_{22} & 0 \\ 0 & 0 & g_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix}$$

Or

$$h_{11,t} = c_{01} + a_{11}\varepsilon_{1,t-1}^2 + g_{11}h_{11,t-1}$$
$$h_{12,t} = c_{02} + a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + g_{22}h_{12,t-1}$$
$$h_{13,t} = c_{03} + a_{33}\varepsilon_{2,t-1}^2 + g_{33}h_{12,t-1}$$

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There are three independent parameters of in each matrix of A_1 and G_1 in the model with two variables and in the model with the variable of n diagonical matrix, each matrix has (n (n +1) / 2) units independent parameters.In the model BEKK GARCH, the fact that coefficients are significant shows the existence of volatility between countries, while it does not show the degree of volatility spilover. It is also possible to achieve the degree of correlation between countries with the CCC GARCH model.

CCC GARCH MODEL

In the CCC GARCH model as in the BEKK GARCH model, modeling process begins by obtaining the average yield equation.

$$r_t = E(r_t \mid \psi_{t-1}) + \varepsilon_t \quad (1)$$

$$Var(\varepsilon_t \mid \psi_{t-1}) = H_t$$

The variance of ε_t which depends on past knowledge is H_t. H_t is strictly positive definite for all t values. The formulation set forth in the following equation allows modeling of both conditional and unconditional variance. All elements of the matrix H_t is shown with $h_{ij,t}$ .In this case the conditional covariance values can be shown as follows;

$$h_{ij,t} = \rho ij \sqrt{h_{ii,t} h_{jj,t}}$$

The values in the CCC GARCH model developed by Bollerslev [12] gives the correlation coefficient between stock market indices. When the model n is generalized for n variable it can be written as follows;

PRELIMINARY ANALYSIS

Multivariate GARCH models are models based on VAR model. Stability of the series is important in this type of models. Therefore, before starting to analyze, the ADF unit root tests were conducted to test the stability of the index return series and as well as of the series.

Table 2: Unit Root Test Results

	NSYE Composite Index	DAX 30	IBOVESPA	SSE Composite Index	CAC 40	HSI	FTSE 100	Nıkkei 225	RTSI	BIST 100
Indice	-1.9498 (0.6278)	-1.6522 (0.7720)	-1.9286 (0.6391)	-1.5702 (0.8046)	-1.8335 (0.6883)	-2.7721 (0.2078)	-2.4351 (0.3610)	-1.8351 (0.6875)	-1.6469 (0.7742)	-3.0691 (0.1139)
Return	-47.882 (0.0000)	-57.9222 (0.0000)	-56.0483 (0.0000)	-56.5667 (0.0000)	-58.8253 (0.0000)	-58.5548 (0.0000)	-49.0519 (0.0000)	-37.1983 (0.0000)	-52.6764 (0.0000)	-56.1662 (0.0000)

Table 2 presents the results of unit root test predictions belonging to the index and return series. Analyzing Table 2 it is observed that indice series are non-stationary and return series are stationary.

Multivariate GARCH models are obtained on the basis of the average return that relates the current return with the previous period's return. Table 3 presents the results of estimation parameters belonging to the average return for each country.

Table 3: Estimated Coefficient From Mean Equation (Diagonal BEKK GARCH)

	NSYE Composite Index	DAX 30	IBOVESPA	SSE Index	CAC 40	HSI	FTSE 100 Index	Nikkei 100 Index	RTSI	BIST 100
Γ	0.00048 (0.0002)	0.00043 (0.0005)	0.00090 (0.0003)	0.00018 (0.4984)	0.00019 (0.0901)	0.00044 (0.0530)	-0.00006 (0.0431)	-0.0001 (0.6066)	0.0010 (0.0009)	0.0007 (0.0056)

Analyzing Table 3 the parameters of stock exchanges for all countries except China and Japan stock exchanges are seen to be significant. That is to say the average return in the current period is determined depending on the yield of the previous period.

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Table 4: Volatility Spillover Estimation (Diagonal BEKK GARCH)

	NSYE Comp Index	DAX 30	IBOVESPA	SSE Index	CAC 40	HSI	FTSE 100 Index	Nikkei 225 Index	RTSI	BIST 100
NSYE Composit Index	0.00112 (0.0000)									
DAX 30	0.00084 (0.0000)	-0.0013 (0.0000)								
IBOVESPA	0.00164 (0.0000)	0.00007 (0.0303)	0.00019 (0.0383)							
SSE	0.00027 (0.0000)	0.00006 (0.9155)	-0.00089 (0.0000)	0.00074 (0.0000)						
CAC40	0.00076 (0.0000)	-0.00101 (0.0000)	0.00031 (0.0000)	0.00044 (0.0000)	-0.0001 (0.0000)					
HSI	0.00041 (0.0000)	-0.0001 (0.0000)	0.00003 (0.6035)	0.00012 (0.0603)	0.00014 (0.0367)	0.00092 (0.0000)				
FTSE 100	0.00150 (0.0000)	-0.00190 (0.0000)	0.00046 (0.0000)	0.00049 (0.0000)	-0.00033 (0.0000)	0.00025 (0.0033)	-0.00030 (0.0000)			
Nikkei 225	0.00128 (0.0000)	-0.00141 (0.0000)	-0.00026 (0.1308)	0.00171 (0.0000)	0.00315 (0.0000)	0.00093 (0.0000)	0.00300 (0.0000)	0.00118 (0.0000)		
RTSI	0.00095 (0.0000)	-0.00077 (0.0000)	0.00027 (0.0199)**	0.00066 (0.0000)	0.0011 (0.0000)	-0.00002 (0.8350)	-0.00137 (0.0000)	0.00037 (0.0008)	0.00057 (0.0000)	0.00070 (0.0000)
BIST 100	0.00070 (0.0000)	-0.00061 (0.0000)	0.00023 (0.0599)***	0.00027 (0.0088)	0.00027 (0.0174)**	0.00020 (0.0774)***	-0.00061 (0.0000)	0.00044 (0.0000)	-0.0009 (0.0000)	0.0011 (0.0000)

** Is significant at the 5% significance level. *** Is significant at the 10% significance level.

Analyzing Table 4 there is no volatility spillover from Germany to China, from Brazil to Hong Kong and from Hong Kong to Russia. The volatility spillover is concerned between the countries remaining outside the specified countries.

Table 5: Effect of Domestic Shock and Past Volatility Spillover Estimation

	NSYE Composite Index	DAX 30	IBOVESPA	SSE Index	CAC 40	HSI	FTSE 100	Nikkei 225	RTSI	BIST 100
A	0.2686 (0.0000)	0.2152 (0.0000)	0.1457 (0.0000)	0.1041 (0.0000)	0.2346 (0.0000)	0.1551 (0.0000)	0.3393 (0.0000)	0.2076 (0.0000)	0.1888 (0.0000)	0.1880 (0.0000)
B	0.9659 (0.0000)	0.9739 (0.0000)	0.9865 (0.0000)	0.9916 (0.0000)	0.9720 (0.0000)	0.9858 (0.0000)	0.9349 (0.0000)	0.9365 (0.0000)	0.9768 (0.0000)	0.9808 (0.0000)

The parameter of A located in the conditional variance equation shows the impact of the countries' past period shocks on the current period of volatility, while the parameter B shows the effect of the past volatility on the volatility of the current period.

Analyzing the results all parameters are seen to be significant. Past period shocks in the country (from the previous period), and the volatility of past period (the previous period) is effective on the current period of volatility.

Table 6: Estimated Coefficient From Mean Equation (CCC GARCH)

	NSYE Composite Index	DAX 30	IBOVESPA	SSE Index	CAC 40	HSI	FTSE 100 Index	Nıkkei 225	RTSI	BIST 100
Γ	8.07046 (0.0000)	0.00115 (0.0000)	0.00116 (0.0000)	2.79615 (0.2771)	9.04145 (0.0000)	7.38125 (0.0006)	5.2481 (0.0022)	5.2853 (0.0793)	0.00210 (0.0000)	0.0016 (0.0000)

Analyzing Table 6 parameters for the stock market of all countries except China are seen to be significant.

Namely the average return in the current period is determined depending on the earning of the previous period.

Table 7: Volatility Spillover Estimation (CCC GARCH Model)

	NSYE Composite Index	DAX 30	IBOVESPA	SSE Index	CAC 40	HSI	FTSE 100 Index	Nıkkei 225	RTSI	BIST 100
NSYE Composite Index	1									
DAX 30	0.60463 (0.0000)	1								
IBOVESPA	0.60835 (0.0000)	0.45694 (0.0000)	1							
SSE Index	0.07959 (0.0000)	0.10180 (0.0000)	0.13342 (0.0000)	1						
CAC 40	0.58737 (0.0000)	0.88154 (0.0000)	0.44186 (0.0000)	0.09472 (0.0000)	1					
HSI	0.25991 (0.0000)	0.27045 (0.0000)	0.26314 (0.0000)	0.05793 (0.0000)	0.27958 (0.0000)	1				
FTSE 100 Index	0.49940 (0.0000)	0.69686 (0.0000)	0.37760 (0.0000)	0.07794 (0.0000)	0.73042 (0.0000)	0.23658 (0.0000)	1			
Nıkkei 225	0.15185 (0.0000)	0.23561 (0.0000)	0.14599 (0.0000)	0.11953 (0.0000)	0.23120 (0.0000)	0.18642 (0.0000)	0.29555 (0.0000)	1		
RTSI	0.32316 (0.0000)	0.44590 (0.0000)	0.34011 (0.0000)	0.12733 (0.0000)	0.46288 (0.0000)	0.21215 (0.0000)	0.43501 (0.0000)	0.21594 (0.0000)	1	
BIST 100	0.25584 (0.0000)	0.35990 (0.0000)	0.28262 (0.0000)	0.08859 (0.0000)	0.36475 (0.0000)	0.18786 (0.0000)	0.33482 (0.0000)	0.14776 (0.0000)	0.37604 (0.0000)	1

Parameters of the CCC GARCH model gives the correlation coefficient between the stock market. Analyzing the results of forecasts, the stock market of countries having the highest correlation with the U.S. are seen to be respectively Brazil, Germany, France and Britain. It is observed that except Brazil there is a weak correlation between the U. S. and other developing countries' stock market. There is a strong correlation between Germany and France. France is followed by Britain, Brazil and Russia. There is weak correlation between Germany and other developing countries' stock market. There is a very low correlation between Chinese stock exchange and that of other countries. The second country which has a high correlation with the French stock market is the UK stock market. Between France and the Russian stock market there is a moderate correlation, and it is observed that there is a low correlation between France and the devoloping countries excluding the Russian stock market.

Although Hong Hong is higher compared to China, it has a weak correlation with the stock market of Japan and Turkey and other countries' stock markets. Russia has the highest correlation with the stock market of Turkey.

The parameter of A located in the conditional variance equation shows the impact of the countries' past period shocks on the current period of volatility, while the parameter B shows the effect of the past volatility on the volatility of the current period.

Table 8: Effect of Domestic Shock and Past Volatiliy Spillover Estimation

	NSYE Composite Index	DAX 30	IBOVESPA	SSE Index	CAC 40	HSI	FTSE 100	Nikkei 225	RTSI	BIST 100
A	0.08981 (0.0000)	0.06858 (0.0000)	0.05313 (0.0000)	0.05942 (0.0000)	0.07455 (0.0000)	0.06015 (0.0000)	0.13112 (0.0000)	0.10202 (0.0000)	0.09197 (0.0000)	0.07684 (0.0000)
B	0.89371 (0.0000)	0.91252 (0.0000)	0.93456 (0.0000)	0.92784 (0.0000)	0.90410 (0.0000)	0.93083 (0.0000)	0.83894 (0.0000)	0.82187 (0.0000)	0.88164 (0.0000)	0.92556 (0.0000)

Analyzing the results all parameter estimates are seen to be significant. Domestic shocks of the countries in the previous period and the previous period volatility have an effect on the current period's volatility.

RESULT

In this study covering the period of 05.01.2000-13.01.2014, daily closing values of 10 countries' stock market index were used and volatility dynamics between countries were examined by using the analyses of BEKK GARCH and CCC GARCH. NSYE Composite Index (USA), FTSE 100 (UK), DAX 30 (Germany), CAC 40 (France), Nikkei 225 (Japan), IBOVESPA (Brazil), SSE Composite Index (China), HSI index (Hong Kong), RTS Index (Russia), BIST 100 (Istanbul) are the stock index included in the analysis.

According to the findings derived from the BEKK model while there is no volatility spillover from Germany to China, from Brazil to Hong Kong, from Hong Kong to Russia, there is a volatility spillover between stock markets of countries in the absence of these groups of countries. However, domestic shocks in the previous period and the volatility of the previous period affect the current volatility period.

According to the findings obtained from the CCC GARCH model, countries having the highest correlation with the United States are respectively Germany, France and Britain. Brazil has the highest correlation with the U.S. among developing countries. There is a weak correlation between the U.S. and other developing countries exchanges. The countries that have been dealt with as having the highest correlation are Germany and France. Although there is not a high degree of correlation between developed countries and developing countries, the country indicating the most differentation among the developing countries is China. The country which has the highest correlation with the stock market of Turkey is Russia. According to the findings it can be said that financial contagion to be discussed for the period and addressed for the groups of countries is more common between developed countries and there is a poor volatility spread between developed countries and developing countries.

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