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THE EFFECTS OF VOLATILITY AND CHANGES IN CONDITIONAL CORRELATIONS IN THE STOCK MARKETS OF RUSSIA AND DEVELOPED COUNTRIES

ABSTRACT: *The aim of this article is to identify patterns of profitability volatility and to establish the degree of dynamic conditional correlation between the stock markets of developed countries and those of Russia. This issue is important for investment strategies and the international diversification of investments. We use the BEKK-GARCH, CCC-GARCH, and DCC-GARCH models and show that the correlation between the Russian stock market and the markets of the USA, UK, Germany, and France has decreased significantly in recent years. We find that while the correlation between the Russian market and the mature European markets is bidirectional, the relationship between the US market and the Russian market is unidirectional. An assessment of the transfer of volatility from all of the mature markets to the Russian market establishes its statistical significance and shows that feedback from the Russian market to the UK and German markets is insignificant. Diversification of international portfolios in the Russian market is recommended.*

KEY WORDS: *volatility, correlation, BEKK-GARCH (1,1) model, DCC-GARCH model, CCC-GARCH model, Russia, developed markets.*

JEL CLASSIFICATION: G15; G17.

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INTRODUCTION

Volatility refers to unexpected changes in stock prices that affect future returns. The main characteristic of any financial asset is its profitability, which is usually considered a random variable. Asset volatility, which describes the distribution of the results of this variable, plays an important role in numerous financial applications. Its main use is to assess the value of market risk. Volatility is also used for risk management and general portfolio management. It is important for financial institutions to not only know the current value of the volatility of managed assets but also to be able to evaluate their future value. Risk management usually measures the potential future losses of an asset portfolio by estimating future volatility and market correlations.

One of the important issues in asset allocation and risk management is establishing the dynamic nature of the interdependence of financial markets. Market research is important for the following reasons. The international diversification of assets depends on close interaction in international stock markets, and the study of market relations establishes the degree of integration. In addition, the degree of integration between the markets of different countries changes over time. In general, most researchers find that an increase in international correlation occurs during periods when the conditional volatility of markets is high. Spreading volatility affects the flow of financial assets between countries and can lead to significant changes in terms of stock market returns, the volume of transactions, and market value.

Stock markets are a good indicator of an economy's health. Although econometric models are used to study stock market financial data, they possess some features – such as leptokurtosis, leverage effects, volatility clustering, and long memory – that cannot be modelled using a linear approach. In the case of a problem of heteroscedasticity in traditional time-series analysis, the application of the least-squares method leads to the parameters becoming statistically insignificant. Therefore, in studies using financial time series it is necessary to use nonlinear models of conditional variance rather than linear time-series models. Models of auto-regression with conditional heteroscedasticity (ARCH) are specially designed to model and predict conditional deviations. To establish time-varying dynamic conditional correlations between the Russian stock market and the markets of developed countries, we use the multidimensional models of generalised auto-regression with conditional heteroscedasticity (M-GARCH) such as the two-dimensional BEKK GARCH, CCC GARCH (constant conditional correlation), and DCC GARCH (dynamic conditional correlation) on the returns of the stock indices S&P500 (USA), FTSE100 (UK), DAX30 (Germany), CAC40 (France), and RTSI (Russia).

The interactions of the US market are of particular interest because, on the one hand, previous studies have shown that the USA is the main driver of Asian and European markets (Al-Zeaud & Alshbiel, 2012) and is also responsible for the transfer of volatility; and on the other hand there is evidence of much less interdependence between the US market and developing countries, including the Russian market (Panda & Nanda, 2018; Wang et al., 2018). Changes in economic policies in recent years have led to changes in the flow and value of commodities and finances, and thus in investors' decisions. However, practically no studies have explored the degree of connection between the markets of developed countries and the Russian market since sanctions were imposed in 2014. Nor has recent empirical research identified the changes in the dynamic correlation and cause–effect relationship between developed markets and the Russian market. The aim of this study is therefore to identify patterns of yield volatility and establish the degree of dynamic conditional correlation between the stock markets of developed countries and Russia. We also model, evaluate, and interpret the secondary effects of volatility in relation to the Russian market.

Empirical research and modern portfolio theory suggest that the benefits of diversification mainly result from a lower correlation of asset returns. Increasing globalisation has created tremendous investment opportunities and the availability of global stock markets has increased substantially, providing investors with significant incentives to seek new investment opportunities and diversify their portfolios in order to obtain higher risk-adjusted returns. This is a further motivation for exploring the time-varying correlation of asset returns.

The study of stock market interaction is also important for portfolio managers who want to obtain higher risk-adjusted returns by diversifying their portfolios with securities from other countries. Although the potential benefits of international portfolio diversification have declined due to the high degree of stock market coverage, investors in developed markets can profit by diversifying their portfolios in emerging markets. Identifying patterns of profitability volatility and establishing the degree of dynamic conditional correlation between stock markets can guide such a diversification of international portfolios in the studied markets.

LITERATURE REVIEW

A large number of empirical applications of volatility modelling are found in both developed (Kutlar & Torun, 2014; Guesmi et al., 2014; Abdelkefi, 2015) and emerging stock markets (Kutlar & Torun, 2014; Guesmi et al., 2014; Salmanov, Babina, Bashirova, Samoshkina, & Bashirov, 2016; Salmanov, Lopatina, Drachena, Vikulina, & Zaernjuk, 2016; Seth & Singhania, 2019; Abdelkefi, 2015). For example, Kutlar and Torun (2014) use BEKK-GARCH and CCC-GARCH analysis, examine the volatility dynamics between the stock markets of developed and emerging market economies. They find that while the markets of developed countries show a strong spread of volatility, there is a weak spread of volatility from developed countries to developing countries. However, internal shocks and volatility in the previous period affect volatility in the current period. Abdelkefi (2015) considers the use of the BEKK-GARCH (1,1) and DCC-GARCH models in assessing the secondary effects of volatility and dynamic conditional correlation between stock indices. She investigates the causal relationship between the stock markets (the Nasdaq and the CAC 40, DAX 30, FTSE 100, Global Dow, Hang Seng, Nikkei 225, Russell 2000, Shanghai, S&P 500, and STOXX 600) using the Granger causality test. The general results show that one-way and two-way relationships exist between the variables and the DCC model coefficients show that there is significant interdependence of all indices, except for the Hang Seng, Shanghai, and S&P 500.

Paramati et al. (2016) examine how the Australian stock market correlates with eighteen border markets in five different regions. The empirical results of the AGDCC-GARCH model show that the correlation of the Australian stock market and the border markets changes over time and that Australia has a weak correlation with all border markets. Panda and Nanda (2018) investigate the volatility of returns and the degree of dynamic conditional correlation between the stock markets of the North American region. Using MGARCH-DCC, they find that emerging markets are less associated with a developed market in terms of profitability and that there is weak joint movement between stock markets.

Seth and Singhania (2019) analyse whether the spread of volatility in border markets affects developed markets. They analyse monthly data from regional border markets for the period 2009–2016 using multidimensional GARCH models (BEKK and DCC). The results show that the selected border markets are not connected. This opens the door to future long-term investment in these markets leading to good returns: long-term investors can benefit from including financial assets in these non-integrated border markets in their portfolios. Guesmi et al. (2014) study volatility in ten European stock markets (Denmark, France, Germany, Ireland, Italy, the Netherlands, Spain, Sweden, Switzerland, and the UK) during financial crises between 1990 and 2012. The results show that most European stock markets are closely related to those of the United States.

Studies related to BRIC countries have examined the influence of volatility expectations and the time-varying conditional correlation between BRIC and US stock markets (Kocaarslan et al., 2017). Ahmad et al. (2018) examine the structure of the dynamic dependence between BRIC countries through the secondary effects of profitability and volatility and Prashan (2014) considers the spread of volatility between BRIC countries

To summarize, several predominant topics emerge from the recent literature. The works reviewed above evaluate the secondary effects of volatility and dynamically estimate conditional correlations between countries. They also consider the use of different models, namely DCC-GARCH and BEKK-GARCH (1,1) and their modifications, and the GJR-GARCH and EGARCH models. Various interdependencies are revealed. Abdelkefi (2015) demonstrates the existence of unilateral and bilateral relations between the US stock market and other developed markets; Panda and Nanda (2018) establish that emerging markets are less related to developed market in terms of profitability; Kutlar and Torun (2014) show that while the markets of developed countries show a strong spread of volatility, in developed countries there is a weak spread of volatility to developing countries; Seth and Singhania (2019) show that selective border markets are intertwined with developed markets; Guesmi et al. (2014) show that most European stock markets are closely related to the US market; Ahmed et al. (2018) use correlation analysis to show a significant positive correlation between developed markets but a relatively insignificant correlation between developing and developed markets; Wang et al.(2018) highlight the presence of a strong spread of volatility from the USA to five major stock markets; Serletis and Azad (2018) reveal statistically significant secondary effects of volatility from emerging economies on the United States; Hung (2019) demonstrates that the correlation between Central European markets is especially significant; and Mitra et al. (2015) find that the transfer of volatility between stock markets is predictable because they follow a certain pattern, and therefore they were modelled using appropriate theoretical distributions. The above articles establish that the process of the spread of volatility affects the flow of financial assets between countries and has led to significant changes in terms of stock market returns, the volume of transactions, and market value. The analyses show that the secondary effects of volatility from mature markets do indeed affect the dynamics of conditional fluctuations in returns in many local and regional emerging stock markets. Further, this indicates that the propagation parameters of volatility change during crises in mature markets.

The interconnections of the Russian stock market have also been widely studied (Anatolyev, 2008; Asaturov et al., 2015; Fedorova, 2013; Saleem, 2008; and Serletis & Azad, 2018), while other authors study the Russian stock market in conjunction with BRIC countries (Ahmad et al., 2018; Kocaarslan et al., 2017; Prashan, 2014). These authors find that financial indicators from Germany – and not from the United States – are the main driving force of the Russian financial markets; that the degree of integration of the Russian stock market with the European stock market is higher than the degree of integration with US and Asian markets (Anatolyev, 2008); that there is direct evidence of a weak connection between the Russian stock market and world markets in terms of profitability and volatility (Saleem, 2008); and that the yield of developed European market indices has a more significant impact on the Russian stock market than on the American or Chinese markets and there is no long-term dependence of the Russian stock market on the dynamics of developed countries (Fedorova, 2013). It is notable that this literature on the interconnections of the Russian stock market uses only one method and none of the studies combines the CCC-GARCH, DCC-GARCH, and BEKK-GARCH (1,1) methods, which is not only limiting but also affects the econometric validity of the conclusions. In addition, no studies investigate the most interesting period when the relationship between markets changed after 2014. There is also an absence of studies on the recent dynamic conditional correlation and volatility between the Russian market and the markets of developed countries. This article tries to fill these gaps by examining the movement of stock markets as they undergo substantial changes due to the financial crisis. It uses GARCH models, which allow variations to change over time and therefore explicitly take into account the conditional volatility in the time-series data.

RESEARCH DESIGN

This section provides a brief discussion of the empirical methodology. In the case of a heteroscedasticity problem in traditional time-series analysis, the predicted efficiency is lost using the least-squares method and the parameters become statistically insignificant. Therefore, in studies conducted with financial time series it is necessary to use nonlinear models of conditional variance rather than linear time-series models.

To evaluate constant and time-varying conditional correlations we use the CCC-GARCH, DCC-GARCH, and BEKK-GARCH (1,1) models and the Granger causality test. Details of these models are presented below.

When the predicted confidence intervals can vary over time, ARCH models are used so that more accurate intervals can be obtained by modelling the variance of the errors; they also allow more effective estimates to obtain the heteroscedasticity in the variance of the errors. In these models the variance of the dependent variable a function of the past values of the dependent variable and independent or exogenous variables. The ARCH models were introduced by Engle in 1982 and summarized as the Bollerslev GARCH (Generalized ARCH) in 1986. These models are widely used in various branches of econometrics, especially when analysing financial time series and are well known in the modelling of stock-return volatility. However, when studying the relationship of volatility between countries a multidimensional GARCH approach is preferable to a one-dimensional approach. Unfortunately, such models can only be estimated by imposing specific restrictions on the conditional variance–covariance matrix (for example, positive definiteness). Most of the problems are addressed in the newer BEKK parameterization (Baba, Engle, Kraft, & Kroner, 1995) proposed by Engle and Kroner (1995). Using quadratic forms to ensure positive definiteness, the BEKK model is consistent with the constant correlation hypothesis and allows the spread of volatility in the markets. However, there is a trade-off between versatility and increasing computational complexity in higher-dimensional systems.

Following Engle and Kroner (1995), the conditional covariance matrix in the BEKK model (1,1) can be written as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'}A + G'H_{t-1}G \tag{1}$$

where H_t is the conditional variance matrix, C is the lower triangular parameter matrix, $\varepsilon_{t-1}\varepsilon_{t-1}^{'}$ is the deviation matrix, A is the parameter matrix in the 2x2 two-dimensional case, which measures the degree to which the conditional deviations correlate with past error squares, and G is the 2x2 parameter matrix, which displays the extent to which current levels of conditional deviations are related to past conditional deviations. The two-way parameterization of BEKK GARCH (1,1) requires an estimate of only 11 parameters in the conditionally dispersive-covariance structure and ensures that the conditional variance (H_t) is guaranteed to be positive for all t. It is important to note that the BEKK model implies that only the magnitude of past innovations is important.

Thus, the second point can be represented as:

$$H_t = C'C + \begin{bmatrix} a_{11} & a_{22} \\ a_{21} & a_{22} \end{bmatrix}^{'} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1,}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1,}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{22} \\ a_{21} & a_{22} \end{bmatrix} +$$

$$\begin{bmatrix} g_{11} & g_{22} \\ g_{21} & g_{22} \end{bmatrix}^{'} H_{t-1} \begin{bmatrix} g_{11} & g_{22} \\ g_{21} & g_{22} \end{bmatrix} \tag{2}$$

This equation for H_t, further expanded by matrix multiplication, takes the following form:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 + g_{11}^2 h_{11,t-1} + 2g_{11}g_{21}h_{12,t-1} + g_{21}^2 h_{22,t-1} \tag{3}$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{12}\varepsilon_{1,t-1}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}^2 + g_{11}g_{12}h_{11,t-1} + (g_{21}g_{12} + g_{11}g_{22})h_{12,t-1} + g_{21}g_{22}h_{22,t-1} \tag{4}$$

$$h_{22,t} = c_{21}^2 c_{22}^2 + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}^2 \varepsilon_{2,t-1}^2 + g_{12}^2 h_{11,t-1} + 2g_{12}g_{22}h_{12,t-1} + g_{22}^2 h_{22,t-1} \quad (5)$$

Multidimensional GARCH models, such as CCC GARCH and DCC GARCH, allow greater flexibility in dispersion specifications. They are based on the use of the following equations:

$$H_t = D_t R_t D_t \quad (6)$$

$$D = diag(h_{11,t}^{\frac{1}{2}} \ldots h_{nn,t}^{\frac{1}{2}}) \quad (7)$$

$$R_t = (\rho_{ij,t}) \quad (8)$$

where R_t is the conditional correlation matrix ρ_t, and the elements D_t, $h^2_{ii,\ t}$ are one-dimensional conditional variances. The covariance is equal to:

$$h_{ii,t} = \rho_{ij,t}\sqrt{h_{ii,t}h_{jj,t}}\,, \qquad i \neq j, \quad (9)$$

The CCC-GARCH model, or the GARCH model with constant conditional correlation, proposed by Bollerslev (1990), is determined by the following equation:

$$H_t = D_t R_t D_t = \rho_{ij,t}\sqrt{h_{ii,t}h_{jj,t}}\,,\ \ i \neq j, \quad (10)$$

whereby the dynamics of covariance depend only on the dynamics of the conditional variances. The number of correlation matrix parameters is n (n-1) / 2.

We are trying to determine how correlated the stock markets are. To measure the time-varying dynamic conditional correlations between the Russian market and the markets of developed countries we use the DCC-GARCH model first proposed by Engle (2002). This GARCH model with dynamic conditional correlation is established in accordance with Equation (7), in which the conditional variance is expressed by the following equation:

$$h_{ii,t} = \omega_i + \sum_{p=1}^{q} a_{ip} a_{i,t-p}^2 + \sum_{p=1}^{j} \beta_{ip} h_{i,t-p}, \quad i = 1,\ldots,n \tag{11}$$

The conditional correlation matrix R_t is defined as the following standardization:

$$R_t = diag(q_{11,t}^{-\frac{1}{2}},\ldots,q_{nn,t}^{-\frac{1}{2}}) Q_t diag(q_{11,t}^{-\frac{1}{2}},\ldots,q_{nn,t}^{-\frac{1}{2}}), \tag{12}$$

where $Q_t = (q_{ij,\,t})$ is a non-symmetric positive definite matrix and has the form:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \tag{13}$$

$\bar{Q}$ is the unconditioned variance matrix u_t c. $u_t = \varepsilon_{it} / \sqrt{h_{ii,t}}$, and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$. Parameter α captures the effect of previous shocks from the current conditional correlation, and parameter β measures the effect of the intrinsic and inter-market past conditional correlation on the current conditional correlation.

According to Engle (2002), the DCC model parameters can be evaluated sequentially in a two-stage approach. First, using Q_t to evaluate conditional correlation:

$$\rho_{ii,t} = q_{ij,t} / \sqrt{h_{ii,t} h_{jj,t}} \tag{14}$$

Second, using $\rho_{ij,\,t}$ to estimate conditional covariance:

$$h_{ii,t} = \rho_{ij,t} \sqrt{h_{ii,t} h_{jj,t}}, \tag{15}$$

where $h_{ii,t}\left(h_{ij,t}\right)$ and $h_{ij,t}$ are the conditional variance and conditional covariance that are generated using one-dimensional GARCH models.

To justify the use of these models, the stationarity of the data series is established by determining the asymmetry and kurtosis; furthermore, unit root tests are performed using the ADF criterion, the ARCH effect test, the Agostino symmetry test, and the Jarque–Bera test for a normal distribution. Next, unconditional correlation coefficients are established for the entire 2010–2019 period and the periods 2010–2014 and 2014–2019. These enable a comparison with the conditional correlation coefficients. The next stage of the study is the use of the Granger test to establish causal relationships between the stock markets.[1] Using the above GARCH models, the estimates of constant correlations for specific time periods, varying dynamic correlations, and coefficients for the matrix of variation–covariances of the two-dimensional BEKK-GARCH (1,1) model are obtained. Descriptive statistics of the data used is given in the Appendix. The following sections analyse and discuss the obtained empirical results.

RESULTS

An augmented Dickey-Fuller Test was performed for data on both indices and profitability; the results are shown in Table 1. Based on the results of the ADF test given, it can be seen that the null hypothesis is accepted for all variables of the series of indices, i.e., the series is non-stationary. Also, for all variables of the yield series there is every reason to reject the null hypothesis of the presence of a unit root for the 1% and 5% significance levels; that is, the series of returns is stationary.

Table 1: Unit root test using the Augmented Dickey-Fuller criterion test

	RTSI	SP500	CAC	DAX	FTSE
Index	–0.359703	2.139663	0.227855	0.858774	0.510405
	(0.5552)	(0.9927)	(0.7522)	(0.8951)	(0.8257)
Profitability	–44.30041	–49.92985	–47.56879	–46.02967	–51.17676
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Table 2 presents the data on the unconditional correlation analysis of the daily quote yield for both the 2010–2019 period and the periods 2010–2014 and 2014–2019. The analysis shows that the correlation between the Russian market and the

1 To determine the direction of causality between stock markets we use the causality test developed by Granger. The question of whether y is the cause of x depends on how much of the current x can be explained by past x values, and then seeing if adding delayed y values can improve the explanation. It is said that x is Granger-caused by y if x can predict better from past values of x and y than from past values of x only. The Granger causality test is conducted for each pair of stock markets,

US market is slightly less than between the Russian market and the markets of the UK, Germany, and France. The analysis by period shows that the correlations decreased significantly for the period 2014–2019 and the correlation with the US market was only 0.35.

Table 2: Correlation of index returns

	2010–2019					**2010–2014**	**2014–2019**
	RTSI	**SP500**	**FTSE**	**DAX**	**CAC**	**RTSI**	**RTSI**
SP500	0.492	1				0.669	0.350
FTSE	0.528	0.768	1			0.660	0.428
DAX	0.539	0.612	0.696	1		0.706	0.413
CAC	0.553	0.629	0.735	0.929	1	0.695	0.443

Before using the ARCH/GARCH model, we need to check whether the model includes ARCH effects. We tested all models for the ARCH effect using the ARCH-LM test; Table 3 shows the results. The null hypothesis of the absence of the ARCH effect is rejected due to very small probability values. The Agostino test for the symmetry of the distribution curve allows us to abandon the null hypothesis and recognize that all the variables have a significant and negative curvature. This suggests that markets respond more to bad news than to good news. Based on the results of the Jarque–Bera test, it is obvious that the p-value is extremely small for all variables, which allows us to reject the null hypothesis regarding the normality of the distribution. All three tests confirm the need for GARCH models.

Table 3: Results of the ARCH-LM test and Agostino test

Variable	ARCH (3) LM c		Agostino test		Jarque–Bera Test	
(profitability)	Statistics	p-value	Statistics	p-value	Statistics	p-value
RTSI	54.61	0.0000	skew= – 0.188z=– 2.248	0.02454	1992.8	0.0000
SP500	88.69	0.0000	skew =– 0.897, z = – 9.379	<2.2e–16	2787.1	0.0000
DAX	48.85	0.0000	skew = – 0.774, z = – 8.336	< 2.2e–16	1623.9	0.0000
FTSE	103.43	0.0000	skew = – 1.211, z = – 11.723	<2.2e–16	7486.8	0.0000
CAC	37.42	0.0000	skew = – 1.067, z = – 10.698	<2.2e–16	2316.0	0.0000

To establish a causal relationship, we performed the Granger causality test. The results and interpretations of the Granger test in terms of the direction of the cause–effect relationships are shown in Table 4 for lags 3 and 4. This shows that the US and UK markets influence the Russian market. This also means that the previous values of the realised volatility of mature US and UK markets have explanatory power to predict the realised volatility of the Russian market. An analysis of the causality of mature markets shows that, with a few exceptions, all mature markets are interconnected. Thus, the US markets affect the markets of France, Germany, and the UK. Moreover, there is a mutual influence between the UK market and the markets of France and Germany. The results indicate the likely existence of a dynamic interaction between mature stock markets to the extent that each market responds to a shock in another. The direction of causality of communication for the periods 2010–2014 and 2014–2019 is generally preserved, with no exceptions (RTSI-DAX for 2010–2014, FTSE-SP500 for 2010–2014, DAX-FTSE for 2014–2019, CAC-FTSE, CAC -DAX for 2010–2014, DAX-CAC 2010–2014).

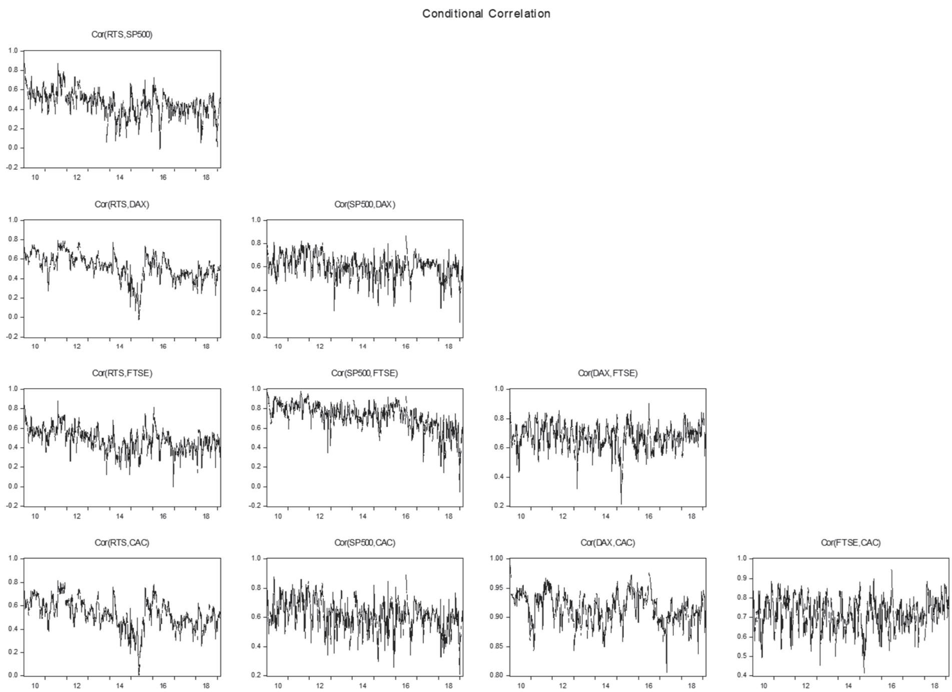
Table 4: Granger causality test results for lags 3 and 4.

Lag	3			4		
The null hypothesis:	**F-statistics**	**Probability**		**F-statistics**	**Probability**	
1	**2**	**3**	**4**	**5**	**6**	**7**
SP500 does not Granger-cause RTSI	14.5821	2.E–09	reject	11.2553	5.E–09	reject
RTSI does not Granger-cause SP500	1.03858	0.3743	do not reject	1.07386	0.3678	do not reject
CAC does not Granger-cause RTSI	0.70024	0.5519	do not reject	0.77477	0.5415	do not reject
RTSI does not Granger-cause CAC	2.53501	0.0552	do not reject	1.71822	0.1432	do not reject
DAX does not Granger-cause RTSI	0.78563	0.5018	do not reject	0.73476	0.5682	do not reject
RTSI does not Granger-cause DAX	1.97795	0.1152	do not reject	1.31257	0.2629	do not reject
FTSE does not Granger-cause RTSI	7.72960	4.E–05	reject	6.39017	4.E–05	reject
RTSI does not Granger-cause FTSE	0.66744	0.5720	do not reject	1.03156	0.3894	do not reject
CAC does not Granger-cause SP500	0.86650	0.4577	do not reject	1.66084	0.1564	do not reject
SP500 does not Granger-cause CAC	39.7874	5.E-25	reject	29.7674	4.E–24	reject
DAX does not Granger-cause SP500	1.17479	0.3179	do not reject	1.86723	0.1135	do not reject
SP500 does not Granger-cause DAX	34.3635	1.E–21	reject	25.8319	4.E–24	reject
FTSE does not Granger-cause SP500	5.77013	0.0006	reject	4.38553	0.0016	reject
SP500 does not Granger-cause FTSE	4.22353	0.0055	reject	3.13897	0.0138	reject
DAX does not Granger-cause CAC	1.63277	0.1797	do not reject	1.20554	0.3064	do not reject
CAC does not Granger-cause DAX	0.64919	0.5834	do not reject	0.86235	0.4858	do not reject

FTSE does not Granger-cause CAC	22.8408	1.E–14	reject	16.8191	1.E–13	reject
CAC does not Granger-cause FTSE	3.19358	0.0227	reject	4.68374	0.0009	reject
FTSE does not Granger-cause DAX	14.3124	1.E–14	reject	10.6182	2.E–08	reject
DAX does not Granger-cause FTSE	4.62727	0.0031	reject	5.86361	0.0001	reject

The correlations according to the BEKK-GARCH (1,1) model are shown in Figure 1. The analysis shows that the correlations of the RTSI with the SP500 and FTSE decrease over time. The correlations of the RTSI with the returns of the DAX and CAC indices also decline, but to a lesser extent.

Figure 1: BEKK-GARCH (1,1) correlations



The conditional correlations using the CCC-GARCH method for the periods 18 January 2010 to 22 February 2019, 18 January 2010 to 6 January 2014, and 6 January 2014 to 22 February 2019 are shown in Table 5. The conditional correlations established by the CCC-GARCH method show that there is less correlation between the US market and the Russian market than between the Russian market and the developed European markets. Comparing the changes in conditional correlations, between the periods 2010–2014 and 2014–2019 the correlation between the Russian market and all other markets in this analysis decreased significantly. The correlation of the Russian market with the US market decreased from 0.64 to 0.33, with the UK market from 0.64 to 0.39, with the German market from 0.67 to 0.41, and with the French market from 0.67 to 0.43.

Table 5: CCC-GARCH conditional correlations

	RTS	SP500	FTSE	DAX	CAC
	During the period 18.01.2010 to 22.02.2019				
RTS	1.000	0.473	0.505	0.524	0.538
SP500	0.473	1.000	0.737	0.612	0.625
FTSE	0.505	0.737	1.000	0.692	0.732
DAX	0.524	0.612	0.692	1.000	0.925
CAC	0.538	0.625	0.732	0.925	1.000
	During the period 18.01.2010 to 06.01.2014				
RTS	1.000	0.645	0.645	0.675	0.672
SP500	0.645	1.000	0.854	0.677	0.687
FTSE	0.645	0.854	1.000	0.710	0.742
DAX	0.675	0.677	0.710	1.000	0.933
CAC	0.672	0.687	0.742	0.933	1.000
	During the period 06.01.2014 to 22.02.2019				
RTS	1.000	0.338	0.393	0.411	0.432
SP500	0.338	1.000	0.632	0.558	0.571
FTSE	0.393	0.632	1.000	0.676	0.722
DAX	0.411	0.558	0.676	1.000	0.921
CAC	0.432	0.571	0.722	0.921	1.000

The dynamic correlation graphs established by the DCC-GARCH model are shown in Figures 2 and 2. These show that the correlation with the European countries also decreased, but by much less. The correlation of the US market with

European markets is marked by a decrease in correlations with the UK market. The correlations between the markets of Germany, the UK, and France do not decrease, the fluctuations are in a rather narrow range, and the connection between the German and French markets is at a very high level.

Figure 2: Dynamic correlation diagrams established by the DCC-GARCH model: RTSI – SP500, RTSI – FTSE, RTSI – DAX, RTSI – CAC

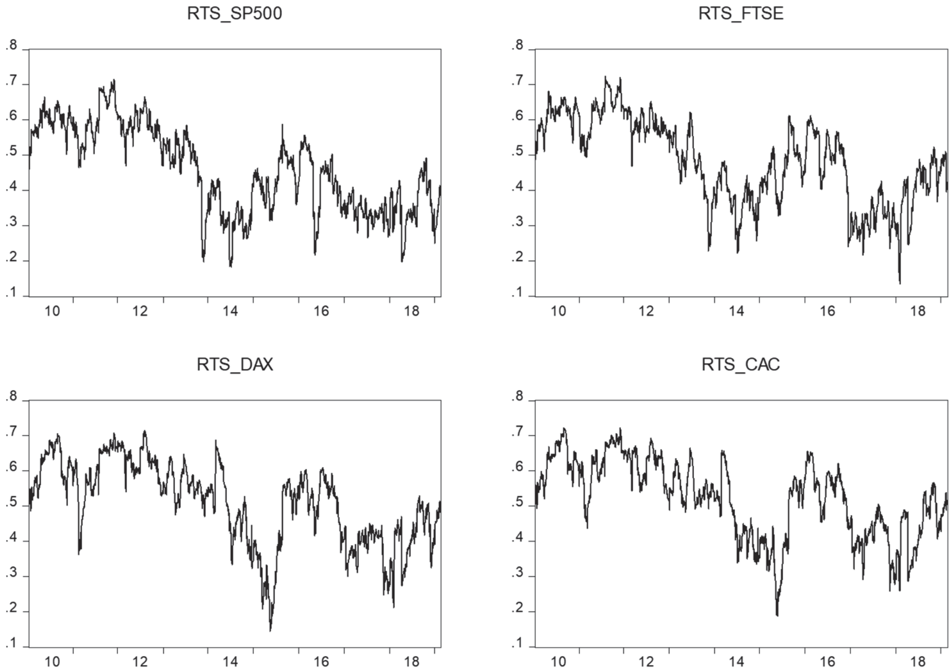
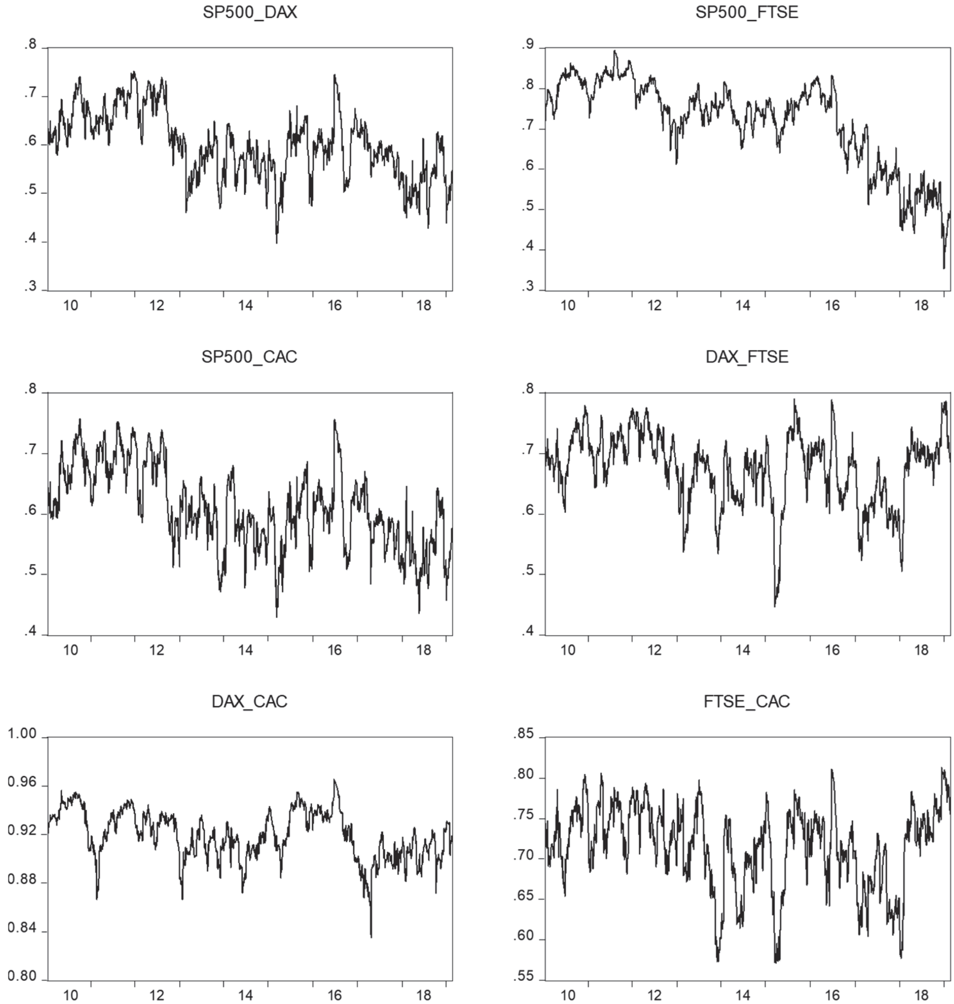


Figure 3: Dynamic correlation diagrams established by the DCC-GARCH model: SP500 –DAX, SP500 – FTSE, SP500 – CAC, DAX – FTSE, DAX – CAC, FTSE – CAC



The results of the estimation of the parameters of the BEKK-GARCH (1,1) model are given in Table 6. The diagonal elements in matrix C represent the average equation, while matrix A reflects the intrinsic and cross-market effects of ARCH. The diagonal elements in matrix G measure the intrinsic and cross-market effects of GARCH. The diagonal parameters C_{11} and C_{22} are statistically significant for the markets of all the countries, which suggests that the profitability of markets depends on their first lags. The estimated diagonal parameters A_{11}, $A_{22,}$ and G_{11}, G_{22} are all statistically significant, which indicates a strong GARCH (1,1) process, leading to conditional deviations of the indices. The off-diagonal elements of matrices A and G capture cross-market effects, such as the spread of shock and volatility between markets.

Table 6: Estimated coefficients for the variation–covariance matrix of the two-dimensional BEKK-GARCH (1,1) model with RTSI for 2010–2019

	SP500		**FTSE**		**DAX**		**CAC**	
	Coeff.	**P**	**Coeff.**	**P**	**Coeff.**	**P**	**Coeff.**	**P**
C_{11}	0.002	0.000	0.003	0.000	0.001	0.001	0.002	0.000
C_{21}	0.001	0.000	0.001	0.000	–0.001	0.291	–0.0002	0.333
C_{22}	0.002	0.000	0.002	0.000	0.001	0.000	0.002	0.000
A_{11}	0.244	0.000	0.237	0.000	0.253	0.000	0.264	0.000
A_{12}	–0.013	0.429	0.047	0.002	0.414	0.000	0.405	0.000
A_{21}	0.362	0.000	0.403	0.000	0.259	0.000	0.275	0.000
A_{22}	0.370	0.000	0.389	0.000	0.251	0.000	0.297	0.000
G_{11}	0.954	0.000	0.952	0.000	0.965	0.000	0.951	0.000
G_{12}	0.019	0.036	0.009	0.327	0.005	0.513	0.0202	0.015
G_{21}	0.912	0.000	0.898	0.000	0.954	0.000	0.952	0.000
G_{22}	0.906	0.000	0.893	0.000	0.960	0.000	0.945	0.000

When analysing shock transmission between the Russian market and other markets, the pairs of off-diagonal parameters A_{12} and A_{21} are mutually statistically significant for RTS and FTSE as well as DAX and CAC. This indicates a bi-directional correlation between the Russian markets and mature European markets. The connection between the US market and the Russian market is unidirectional. Shocks are not transmitted from the Russian Federation to the USA since the off-diagonal parameter is not statistically significant.

An assessment of the transfer of volatility based on the off-diagonal parameters G_{12} and G_{21} shows the statistical significance of the transfer of volatility from all mature markets to the Russian market, the insignificance of the feedback from the Russian market to the markets of the UK and Germany, a significance at the 5% level with the markets of the USA and France, and their insignificance at the

1% level. This indicates a weak integration of the Russian market with the markets of other countries examined in this analysis.

The results of the assessment of the BEKK-GARCH (1,1) model with the RTSI for the period 18 January 2010 to 6 January 2014 are shown in Table 7, and for the period 6 January 2014 to 22 February 22 2019 in Table 8.

Table 7: Estimated coefficients for the variation–covariance matrix of the two-dimensional BEKK-GARCH (1,1) model with RTSI for 18 January 2010 to 6 January 2014

	SP500		FTSE		DAX		CAC	
	Coeff.	**P**	**Coeff.**	**P**	**Coeff.**	**P**	**Coeff.**	**P**
C_{11}	–0.003	0.000	0.003	0.000	0.002	0.000	0.003	0.000
C_{21}	–0.001	0.0347	0.001	0.269	–0.001	0.359	–0.001	0.134
C_{22}	0.002	0.000	0.002	0.000	0.002	0.00	0.002	0.000
A_{11}	0.211	0.000	0.099	0.000	0.219	0.000	0.206	0.000
A_{12}	0.034	0.358	0.080	0.009	0.386	0.000	0.292	0.000
A_{21}	0.359	0.000	0.407	0.000	0.323	0.000	0.327	0.000
A_{22}	0.329	0.000	0.381	0.000	0.279	0.000	0.293	0.000
G_{11}	0.964	0.000	0.925	0.000	0.961	0.000	0.963	0.000
G_{12}	0.058	0.036	0.089	0.000	0.064	0.083	0.152	0.000
G_{21}	0.913	0.029	0.899	0.000	0.932	0.000	0.924	0.000
G_{22}	0.919	0.000	0.899	0.000	0.945	0.000	0.937	0.000

The analysis of the coefficients of the BEKK-GARCH (1,1) model with the RTSI for the period 18 January 2010 to 6 January 2014 (Table 7) shows that the diagonal parameters C_{11} and C_{22} are statistically significant for the markets of all the countries. The estimated diagonal parameters A_{11}, A_{22} and G_{11}, G_{22} are also all statistically significant. The off-diagonal elements A_{12} and A_{21} indicate a bi-directional correlation between the Russian market and mature European markets, while the connection between the US market and the Russian market is still unidirectional: shocks are not transferred from the Russian Federation to the USA. The off-diagonal parameters G_{12} and G_{21} show the statistical significance of the transfer of volatility from all mature markets to the Russian market, and the insignificance of the feedback from the Russian market to the German market.

Table 8: Estimated coefficients for the variation–covariance matrix of the two-dimensional BEKK-GARCH (1,1) model with RTSI for 6 January 2014 to 22 February 2019

	SP500		FTSE		DAX		CAC	
	Coeff.	**P**	**Coeff.**	**P**	**Coeff.**	**P**	**Coeff.**	**P**
C_{11}	0.002	0.000	0.003	0.000	0.003	0.122	0.002	0.000
C_{21}	0.0004	0.271	0.001	0.000	0.000	0,057	0.001	0.056
C_{22}	0.002	0.000	0.002	0.000	0.001	0.000	0.002	0.000
A_{11}	0.242	0.000	0.284	0.000	0.282	0.000	0.297	0.000
A_{12}	–0.081	0.007	0.092	0.095	0.200	0.018	0.148	0.000
A_{21}	0.403	0.000	0.451	0.000	0.267	0.000	0.329	0.000
A_{22}	0.421	0.000	0.436	0.000	0.216	0.000	0.298	0.000
G_{11}	0.958	0.000	0.946	0.000	0.946	0.000	0.944	0.000
G_{12}	0.063	0.000	–0.003	0.917	0.200	0.000	–0.041	0.011
G_{21}	0.889	0.000	0.853	0.000	0.957	0.000	0.935	0.000
G_{22}	0.878	0.000	0.859	0.000	0.969	0.000	0.944	0.000

The analysis of the coefficients of the BEKK-GARCH (1,1) model with the RTSI for the period 6 January 2014 to 22 February 2019 (Table 8) shows that the diagonal parameters C_{11} and C_{22} are statistically significant for the markets of all the countries. The estimated diagonal parameters A_{11}, A_{22} and G_{11}, G_{22} are also all statistically significant. The off-diagonal elements A_{12} and A_{21} indicate a bi-directional correlation between the markets of the Russian Federation and the markets of the USA, Germany, and France, while the connection of the UK market with the Russian market is unidirectional: shocks are not transmitted from the Russian Federation to the UK. The off-diagonal parameters G_{12} and G_{21} show the statistical significance of the transfer of volatility from all mature markets to the Russian market, and the insignificance of the feedback from the Russian market to the UK market. Comparing the values of the off-diagonal coefficients by period, we can see that their changes are insignificant. A comparison of the values of the coefficients shows that the influence of the volatility of developed countries on the current volatility of the Russian market is much greater than vice versa; that is, it is more influential.

DISCUSSION

The analysis of impact causality using the Granger test shows that the US and UK markets influence the Russian market. This means that the previous values of the realised volatility of mature US and UK markets have explanatory power for predicting the realised volatility of the Russian market.

The conditional correlations established by the CCC-GARCH method (as well as the unconditional correlations) show that the correlation of the Russian market with the US market is less than with the developed European markets. This result is consistent with previous studies of the Russian market's relationships (Anatolyev, 2008; Fedorova, 2013). Comparing the analysed changes in conditional correlations of all markets in the period 2010–2014 with those in the period 2014–2019 shows that the correlation between the markets of developed countries and the Russian market decreased significantly. This finding confirms our hypothesis, so it can be argued that a great opportunity has emerged for profitably diversifying international portfolios in the Russian market.

Analysis of the correlation graphs using the BEK-GARCH (1,1) model reveals that the correlation between the RTSI and the SP500 and FTSE has decreased over time. The correlation between the RTSI and the returns of the DAX and CAC indices has also declined, but to a lesser extent.

The dynamic chart of the correlation between the Russian market and the US market established by the DCC-GARCH method shows that between 2010 and the beginning of 2019 the correlation almost halved. There has also been a decrease in correlation between the Russian market and European markets, but it is much less. The correlation between the US market and European markets has been marked by a decrease in correlations with the UK market. The correlations of the markets of Germany, the UK, and France have not decreased, the fluctuations are in a rather narrow range, and the connection between the German and French markets is at a very high level. This result is consistent with the estimates of other studies (Guesmi et al., 2014; Abdelkefi, 2015).

CONCLUSION

This is the first study of the Russian market that uses the multivariate GARCH-BEKK along with the CCC-GARCH and DCC-GARCH models. In establishing the trends in conditional correlation and volatility between the markets of Russia and developed countries, this study contributes to the existing literature on the secondary effects of volatility and conditional correlation in financial markets.

The evaluation of the parameters of the two-dimensional BEKK-GARCH model (1,1) establishes a bi-directional correlation between the Russian market and mature European markets. The connection between the US market and the Russian market is unidirectional: shocks are not transferred from the Russian Federation to the USA. The assessment of volatility transfer establishes the statistical significance of the transfer of volatility from all mature markets to the Russian market, and the insignificance of the feedback from the Russian market to the markets of the UK and Germany. This indicates that the Russian market is weakly integrated with the markets of the other countries in this analysis.

Our study reveals the interdependency of the markets of Russia, the USA, the UK, Germany, and France. A decrease in the dynamic conditional correlation coefficients was observed, which was confirmed by the results of the estimation using CCC-GARCH, two-dimensional BEKK-GARCH (1,1), and DCC-GARCH models. Our study is consistent with the literature that finds that the US market is not the most influential market for Russia.

The fact that the correlation between the markets of Russia and developed countries has significantly decreased since the imposition of sanctions in 2014 has provided an opportunity to profitably diversify international portfolios in the Russian market. The results of our study present an opportunity for portfolio managers, financial analysts, and financial authorities to better understand the volatility of the flows and the relationships between stock markets.

The study is limited by the fact that it examines only a small number of markets. To explain the parameters of the effects of volatility and to establish a complete picture of the effects of volatility at different time periods using various methodologies, future research could study the relationship between the Russian market and more European markets, as well as the markets of Turkey and China.

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APPENDIX: DESCRIPTIVE STATISTICS

This article uses daily observations of the following stock exchanges: S&P500 (USA), FTSE 100 (UK), DAX 30 (Germany), CAC 40 (France), and RTSI (Russia), covering the period 18 January 2010 to 22 February 2019. We use profitability to indicate a proportional price change over the range of stock indices. Profitability is defined as the natural logarithm of the ratio of the current price to the previous value. The descriptive statistics are shown in Table A1. All series have negative asymmetry and a high positive excess. These values indicate a situation in which the distribution of the rows has a long left tail and is leptokurtic. Diagrams indicating the exchange indices and their profitability are presented in Figures A1 to A5.

Table A1: Descriptive statistics

	RTSI	SP500	FTSE	DAX	CAC
Average	–0.000123	0.000386	0.000116	0.000283	0.000114
Median value	0.000479	0.000491	0.000321	0.000751	0.000323
Maximum	0.132462	0.056929	0.084216	0.052104	0.092208
Minimum	–0.132545	–0.068958	–0.083989	–0.070673	–0.083844
Standard deviation	0.017419	0.009459	0.010328	0.012167	0.012560
Asymmetry	–0.501879	–0.418426	–0.336624	–0.264158	–0.155799
Kurtosis	10.82471	8.025820	9.927537	5.666349	7.125334
Sum	–0.282684	0.887036	0.266292	0.667791	0.262993
Observations	2,298	2,298	2,298	2,298	2,298

Figure A1: The RTS index and its profitability

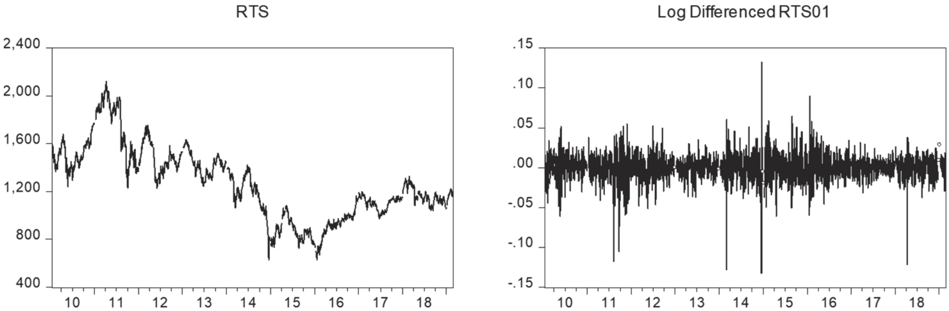

Figure A2: The S&P500 index and its profitability

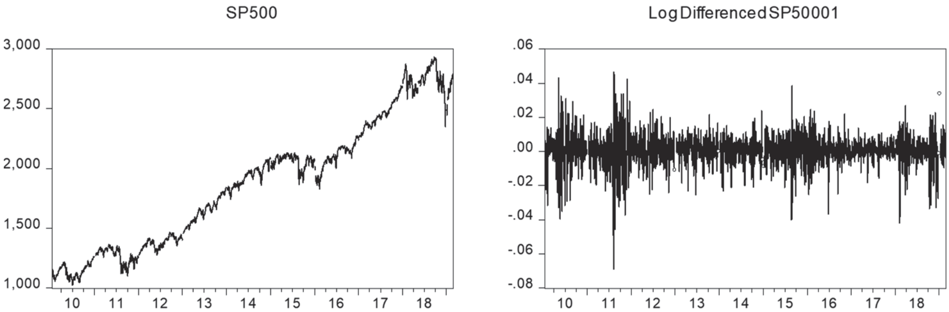

Figure A3: The DAX index and its profitability

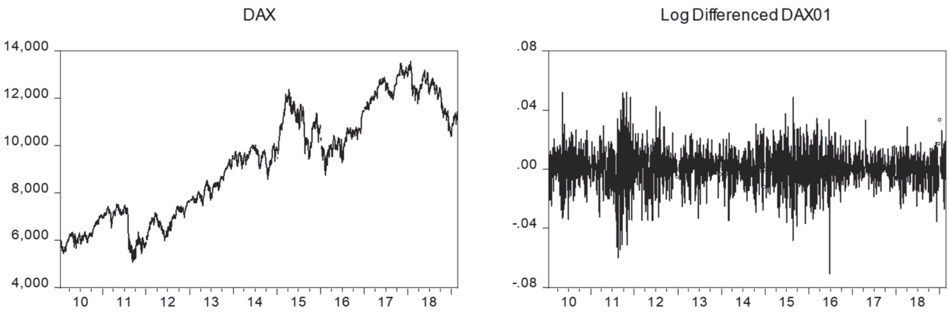

Figure A4: The FTSE index and its profitability

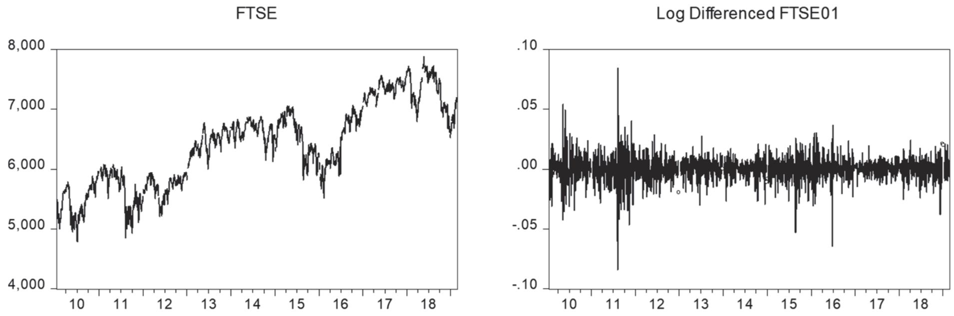

Figure A5: The CAC40 index and its profitability