OIL PRICE AND THE RUSSIAN STOCK MARKET VOLATILITY

By

Anton Pak

THESIS

Submitted to
KDI School of Public Policy and Management
in partial fulfillment of the requirements
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ABSTRACT

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This paper investigates the effect of oil prices on the Russian Stock market fluctuations using the GARCH (1, 1) model. Since Russian economy and financial system highly depends on oil and gas prices, the determination of the linkages and the degree of dependency between markets are key points examined in the paper. The aim of this thesis is to study the effect of the Brent oil logarithmic returns to forecast the fluctuations of the RTS Index returns on the Russian financial market. The findings of this thesis concentrate on the existence of volatility transmission from the oil return's movements to the future volatility of the RTS Index returns. I found that the results from the Augmented Dickey-Fuller Test show that the Brent oil price and RTS Index time series data are stationary meaning the mean and autocovariances values do not depend on time. The Granger Causality test proves the one-directional linkage of the Brent oil returns causing movements in the RTS Index values. The Johansen Cointegration Testing procedure using an Unrestricted Cointegration Rank Test (trace statistic technique) indicates that there is possibly a long-run association between oil and stock returns meaning the variables may share common stochastic movements. The GARCH (1, 1) model provides significant results in the case of volatility testing between oil and stock markets returns. The use of oil price fluctuations, past information of the RTS Index return's behavior and the Index's past variance help to forecast future fluctuations.

Dedicated to my beloved family and friends

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ABBREVIATIONS

AIC	Akaike Information criterion
ARCH	Autoregressive conditional heteroskedasticity
CIA	Central Intelligence Agency
FSSS	Federal State Statistics Service of the Russian Federation
GARCH	Generalized Autoregressive conditional heteroskedasticity
GED	Generalized error distribution
GDP	Gross domestic product
MICEX – RTS	Moscow Interbank Currency Exchange – Russian Trading System
OLS	Ordinary Least Squares
REBCO	Russian Export Blend Crude Oil
RUB	Ruble
SIC	Schwarz Information criterion
USD	United States Dollars
VAR	Vector Autoregression model
VARMA	Vector Autoregressive Moving-Average
WTI	West Texas Intermediate

1. INTRODUCTION

Russia has experienced significant political, economic and social transformations since the breakdown of the Soviet Union in 1991. The initial transition from the isolated, centrally-planned economy to the globally integrated, market economy was implemented through economic reforms and privatization later in the 1990s. Russia is the largest country in the World in terms of land and it is the 9th largest economy in terms of nominal GDP (World Bank 2012b). Russia is a large, fast-growing economy and the economy has grown on average at 7% for a decade since the 1998 Russian financial crisis resulting in the emergence of the middle class and political stability (World Bank 2012a). The economic growth was driven at large by rising commodity prices on the global markets and oil export volume, consumer and government spending, macroeconomic stability and smooth ruble fluctuation. The Russian economy and the federal budget remain highly dependent on revenues coming from oil and gas industries. Even though the Russian government established a policy trying to avoid increasing dependency on oil revenues, the increase in government spending on military and social welfare programs rather than industrialization made it difficult to turn the economy away from the oil cash inflows. Thus, according to the CIA World Factbook, “In 2011, Russia became the world's leading oil producer, surpassing Saudi Arabia; Russia is the second-largest producer of natural gas; Russia holds the world's largest natural gas reserves, the second-largest coal reserves, and the eighth-largest crude oil reserves” (CIA 2012).

Mostly due to the increasing oil and gas revenues, the Russian economy had been developing at a fast rate. However, it got severely hit by the 2008-09 global economic crisis. The decline in oil prices and other Russian export commodities, and the shortage of foreign credits on the market for Russian banks and companies triggered the sharp drop in the economy. The

Russian Stock Market fell by over 75% from its maximum level, the ruble depreciated by more than 45% from August 2008 to April 2009, the Russian GDP declined by 7.9% in 2009, and the unemployment rose to 9.4% (FSSS 2012).

In order to ease the effect of the crisis on the economy, the Russian government adopted the anti-crisis spending plan in 2008-2009 which totaled approximately 6.7% of GDP. Simultaneously, the Central Bank of Russia spent $157Bn. or 27.5% of the international reserves, in 2008-2009 to decelerate the ruble's devaluation. The government also injected into the Russian banking and financial system the equivalent of $200 billion in cash to increase liquidity and help Russian firms to service their debt payments in foreign and national currencies.

The global economy and international markets started to recover in the third quarter of 2009, as did the Russian economy. The inflow of direct and portfolio investments into the Russian Federation, increase of liquidity in the financial market, consistent low interest rates on foreign markets, and rising demand on commodities on international markets moved the macroeconomic indicators upward. Unemployment and inflation in Russia have been steadily decreasing since mid-2009 and the government has been able to reduce social tensions using oil revenues.

The Russian economy and the Russian Federal Budget are highly dependent on major commodity prices, as is the case with the Russian Stock Market. More than 50% of the RTS Index value emanates from major oil and gas companies quoted on the MICEX-RTS Stock Exchange, prices of which are largely determined by the situation on the international oil market (MICEX-RTS 2012). The dependency of the Russian stock market on the oil price market is clear in the long-run, since the trends in oil prices affect the macroeconomic indicators of the

Russian economy and economic well-being of the Russian oil conglomerates, but in the short-run, the association of both markets' movements is still unclear.

Extensive research has been done on the linkages between oil and stock markets and the importance of their interconnection in oil-importing as well as oil-exporting countries. This paper will examine the volatility relationship between the oil and stock market in Russia using the fluctuations in returns for both markets. An analysis on between-markets volatility can provide important insights to the degree of trend significance, and information on pricing valuations. The Russian stock market has fluctuated significantly, especially, in the period of crises and high instability on international markets. Therefore, it is important to apply volatility models with strong forecasting power to determine variables that influence assets' prices the most. The importance of volatility modeling is growing rapidly, because volatility measures are used to price different derivatives, calculate hedge ratios, and run risk management analysis.

From the reviewed literature, it is apparent that a wide array of techniques has been applied to test the volatility of oil prices and stock market returns. Most volatility forecasting models are based on the GARCH-type models with different specifications which take into account the stochastic variance and past innovations as major contributors to volatility forecasting. Hou and Suardi (2012) argues that "Despite extensive studies to identify the most appropriate GARCH model which provides the best out-of-sample forecasting performance, there is no model that consistently dominates the other" (618). Arouri, Jouini and Nguyen (2012) examined the volatility spillover between data series through VAR (1)-GARCH (1, 1) finding significant results of volatility spillover with regard to shocks on oil and stock markets. Hou and Suardi (2012) proposed to apply nonparametric GARCH modeling to forecast the volatility of oil price returns, arguing that a smoothing technique in the model would generate better estimates for lagged regression errors and variances. This paper uses a simple GARCH model proposed by Bollerslev (1986) and based on the ARCH model developed by Engle (1982), to investigate the volatility relationship between oil and stock markets in an oil-exporting country like Russia. The significance of this paper lies in the financial understanding of how much the volatility of oil returns in the international oil market is responsible for the degree of fluctuation in the Russian stock market.

The GARCH (1, 1) model in this paper examines volatility dependencies and determines the exogenous factors that may influence the volatility of the stock market returns. The application of the model together with macroeconomic indicators provides advantages to analyze volatility dependency between variables, so that past variances of the exogenous variables help predict volatility patterns over time. The stochastic model projects the RTS Index logarithmic returns volatility in the correspondence with the Brent oil price logarithmic returns on the weekly basis observations. The Augmented Dickey-Fuller Test is used to perform data analysis, since the data are required to be stationary in order to use the GARCH model.

The empirical results of this thesis provide 4 main findings. First, there is at most one long-run association between oil price daily returns and the RTS Index daily returns. Second, the volatility of the oil price returns causes fluctuations in the RTS Index returns and these dynamics are significant. Third, the past innovations, lagged variances of the Index and the volatility of oil prices returns explain the volatility of the Index. It can be translated into the influence of projecting power of the oil market onto future volatility values of the Russian stock market, even when a low level of significance is in place. Forth, along with the Brent oil returns, such endogenous variables as the USD/RUB exchange rate and industrial production have explanatory power and contribute to the future volatility of the RTS Index returns.

These findings can be used in the following research to work on the pricing models for derivatives, establish hedge ratios for different sectors in portfolio investment and improve risk management in oil stock investment. The further research on volatility transmissions between different financial markets in Russia will help to establish efficient price setting on equities, bonds and derivatives and improve asset management. The comparisons of the volatility results in other developing and developed countries that have similar economic conditions may provide insights on effective commodities policies on wealth distribution and its utilization.

The following sections are organized as follows. Section 2 examines theoretical background of volatility techniques, investigates interdependence of the oil and stock markets and summarizes the findings of the previous research papers on the factors that influence stock markets' behavior. Section 3 provides econometric frameworks and data description for the tests that were used in the research as well as summary statistics of the data. The following section includes the analysis of the empirical results, their possible limitations and further discussions on the matter. Section 5 concludes this thesis paper.

2. Literature Review

The world's dependence on oil prices has grown greatly over the past several decades. Prices of energy resources influence the development of the world economy, and the economic well-being of many countries. Oil is an important factor of production in modern economic systems. That's why many theoretical studies and empirical evaluations have been done to analyze the oil market and its impact on an economy. Volatility in oil prices and its effect on economic and financial markets have recently become an important area of study to financial institutions and market players, "not least because they affect decisions made by producers and consumers in strategic planning and project appraisals, but also they influence investors' decision in oil-related investments, portfolio allocation and risk management" (Hou and Suardi 2012, 618). Instability in oil prices makes it hard to predict and build forecasts in production and costs functions, which affect government monetary and fiscal policies.

Many studies have investigated the dependence of an economy on oil prices. Hamilton (1983), Gisser and Goodwin (1986) provide evidence on negative correlation between oil prices and economic output through testing the causality effect of increasing energy commodities prices on economic recessions. Also, in the article written by Huntington (1986) and in the research conducted by Cologni and Manera (2006), an asymmetric relationship between oil prices and macroeconomic indicators was investigated. Increase in oil prices tends to diminish economic output more than decrease in oil prices can stimulate economic activities. Furthermore, Lee, Kang, Ratti (2011) and Henriques and Sadorsky (2011) provide empirical evidence that the volatility of oil futures increases market and macroeconomic uncertainty, which leads to deference of investments and decline in economic and financial activities, including financial markets.

The existence of a relationship between oil price and stock market returns seems not to be surprising. The economic explanation lies in the potential effect of oil prices on corporate cash-flows in terms of both costs and revenues. In different companies, fluctuations of oil prices may have a positive or negative impact depending on whether a company is a net producer or a net consumer of oil products. According to Arouri, Jouini and Nguyen (2012), “The extent to which companies may be affected by oil prices can be explained by referring to the theory of equity valuation where stock price is obtained by simply discounting all expected future cash-flows at the investors’ required rate of return” (611). Oil prices themselves are not the only factor that drives companies’ valuation; the extent of how quickly prices change and by what percentage (volatility) also play a significant role in value determination.

Vo (2011) found that the daily volatilities in the oil prices and the returns in S&P500 are persistent, and can be predicted over time based on past variances of the data variables. It is also noted that the volatility effects are bidirectional between the two markets and the increasing volatility on the one market increase volatility on the other over time. But, even though volatilities are highly interdependent, the correlation between the stock and oil markets varies significantly in times of increasing volatilities. In order to provide those findings, the multivariate stochastic volatility (MSV) model was used that assessed the interaction between oil and stock markets. The Vo’s MSV model through application of dynamic correlation techniques showed that:

> On average, when the stock market increases by 1%, oil futures price increases roughly by .19% the next day, other things being equal. On average, when oil futures return increases by 1%, the broad stock market index decreases approximately by .02% the next day, other things being equal. On average, a shock that increases the volatility in the oil

market by 1% will increase the volatility in the stock market by about .014% a day later, other things being equal. (960)

Also, the bivariate VAR (1) with stochastic volatility was applied to measure the volatility transmission from one market to another during shocks and crises. Vo's paper concludes that if the external shock causes the volatility of the S&P500 to move by 1%, it will raise the volatility of oil prices by 0.027% a day later.

The assumption of the oil price fluctuations cause stock price movements may be contradictory, if the work of Kapusuzoglu (2011) taken into account in which the one-way causality relationship from the values of 3 indices of the stock exchange to oil prices was observed through the application of the Granger causality Test. At the same time, however, the change in oil prices did not cause the fluctuations of the stock prices. "As a result of applied Johansen co integration test, it was determined that there was a co integrated relationship between each index and oil price, with other words, there was a long term relationship between each of the three index and oil price" (99).

The increasing use of simple ARCH and GARCH models, developed by Engle (1982) and Bollerslev (1986), to evaluate volatilities and to forecast them inspired other econometricians to develop modified versions of those models to improve the results in a variable assessment. Arouri, Jouini and Nguyen (2012) used the VAR(1) – GARCH(1,1) model to estimate the volatility spillover between oil prices and oil stock prices in Europe. This model allows running a multivariate analysis of conditional volatility of the time series data and evaluating the cross effects and volatility transmission of time series datasets. Also, it generates good predictions of the model's unknown parameters while keeping the model rather simple. The model showed that the estimates of the ARCH (1) and GARCH (1) coefficients of the oil prices and European oil stock companies in the conditional variance equations are statistically significant at the conventional levels of significance. But, at the same time, “the autoregressive terms corresponding to stock return equations are not significant in all cases” (614). In Europe, the results of the analysis show that the volatility transmission is unilateral from oil prices to stock market; this conclusion is based on the observed spillover effects during crises and shock situations, while the volatility spillovers during the times of stability does not seem significant.

Since the stock markets in the developed countries are usually less dependent on one single factor, e.g. oil prices, and more diversified in nature than stock markets in emerging economies with rapidly developing financial systems, the research of the volatility spillover effects on emerging stock markets may bring different causal results. Masih, Peters and Mello (2011) argue in the academic article “Oil price volatility and stock price fluctuations in an emerging market: Evidence from South Korea” that the oil price movements significantly affect the South Korean stock market. Due to the fact that South Korea is a big importer of oil and the country’s industrial capacity is highly dependent on oil and subsequent oil products, the fluctuation of oil prices can have a major impact on the companies’ cost structure (975). The cost effect is later transmitted to the valuation of the major conglomerates and production companies that are quoted in the Korea Stock Exchange. Also, interest rates and industrial production as exogenous variables have impact on the stock market fluctuations. The results of the oil prices’ volatility effects on the real stock returns were obtained through the application of the Vector Auto regression Model (VAR). In addition to the VAR methodological framework, the Granger Causality Test was performed among oil prices and real stock returns to establish the causal link between the international oil market and the Korean stock market. The hypothesis was accepted that fluctuations in the oil market cause changes in the Korean stock prices, but not vice versa.

The Korean example demonstrates the oil price volatility impact on the oil-importing country and its stock market. Some researchers have also examined the effect of oil prices' volatility spillovers on oil-exporting countries' economies and stock markets. Rahman and Serletis (2012) investigate the impacts of oil price fluctuations and uncertainty on production output in Canada. Through the bivariate VARMA, GARCH-in-mean and asymmetric BEKK model using the data of inflation, interest rates, levels of consumption and production, capital liquidity, market confidence on stock prices, the authors have concluded that there is "an asymmetry in the effects of oil price shocks on real activity although the evidence of asymmetries in the conditional variance–covariance matrix does not necessarily translate into asymmetries in the propagation mechanism" (609). Another conclusion derived from the econometric models stated that as the uncertainty about the fluctuations in oil prices grow, the growth rate of the real economic activity in Canada decline. This conclusion is also supported by Hamilton (1996) on factors that have predictive power with oil price changes and their effects on macroeconomic and financial markets. Hamilton provides evidence that external shocks such as economic crises and political disturbances in oil-producing countries cause significant macroeconomic consequences, especially, for oil-exporting countries. The macroeconomic misbalances are cleared through financial markets in terms of increased equity and stock prices in times of upward volatility spillovers.

Rahman and Serletis (2012) concentrated their research on the effect of fluctuations of oil prices on real economic output, while Aouri, Jouini and Nguyen (2012) examined the effect of oil price fluctuations on the stock prices of oil exporting economies. Similar to the effect of the oil prices fluctuations on the real output, the lagged oil price returns have strong impacts on stock market returns in the cases of Bahrain, Oman and Qatar. The findings show that the estimates of ARCH and GARCH coefficients in the variance and mean equations are significant and the null hypothesis cannot be rejected at conventional levels (614). This justifies that past values of the residuals and the previous variances of the values can serve to forecast future volatility dynamics. Using a VAR(1)-GARCH (1, 1) model, the authors evaluated the strengths of the return linkages and volatility transmission for the Gulf Cooperation Council Countries to determine how strongly the oil price fluctuations affect stock returns in each country and what are the exogenous factors that may explain the volatility spillover. Due to the strong linkages of oil and equity returns in the region, the probability of gaining a required rate of return in case of investing in both markets is estimated, risk distribution between assets are discussed and portfolio strategy and hedging opportunities are advised to be considered to utilize the return and volatility spillovers of the markets.

As for the Persian Gulf Countries, the causality effects from oil prices to the stock markets and accumulated wealth may be observed in the Norwegian stock market and Norwegian economy. Bjornland (2008) concludes that higher oil prices have a positive impact on the Norwegian oil export-oriented economy. The results show that a 1% in oil price increase produces 0.2-0.3% in immediate increase in stock returns and provides effect of 0.4-0.5% in the long-run. Also, “the Norwegian economy responds to higher oil prices by increasing aggregate wealth and demand. As a consequence, the unemployment rate falls and inflation picks up gradually. In response to increased economic activity, the interest rate is eventually increased” (26).

Research presented in this work investigates the volatility interrelation between world oil prices and the Russian stock market. Researchers have been studying the effect of oil markets on the Russian economic and financial wealth. Ito (2010) provides empirical results of the effect of oil price fluctuations on macroeconomic indicators utilizing the VAR model developed by Sims (1980). Ito (2010) has found that "a 1% increase (decrease) in oil prices contributes to the depreciation (appreciation) of the exchange rate by 0.17% in the long run, whereas it leads to a 0.46% GDP growth (decline)" (8).

Bhar and Nikolova (2010) utilized the bivariate EGARCH model to analyze the volatility relationship between global oil prices and equity returns in the Russian Stock market. The effect of the WTI oil price fluctuations and its past innovations is proven to be significant on stock returns and conditional volatility in the Russian equity market. At the same time, the model does not provide sufficient evidence to conclude that the oil price variance has a contribution to the stock index volatility. Nevertheless, "there is evidence of statistically significant and negative periodical conditional correlation between the AK&M Composite and WTI returns, which confirms the dependence of Russian equity market returns on oil prices" (182).

The topic of volatility dependencies and transmissions between oil and stock markets has been studied in the cases of many oil-importing and oil-exporting countries, but a research on the Russian case is very limited. Compared to previous studies, this paper examines volatility relationship between oil and the Russian stock market utilizing the GARCH (1, 1) model. In most papers I have studied authors applied the GARCH-type model to test factors that influence volatility behavior of a dependent variable.

My review of the literature has suggested several gaps that my further research will help to fill. This thesis offers insights on the exogenous factors may possess explanatory power and understanding of linkages between oil price fluctuations and the Russian stock market volatility through the cointegration and causality analysis.

3. Methodology and Data

3.1. Data Description

There are 2 variables that are used to examine price volatility dependency: the Brent oil price and the Russian Trading System (RTS) Index values.

Russia is one of the largest crude oil exporters in the world and it exports several sorts of oil depending on the place of oil extraction and the proportion of light hydrocarbons in the petroleum mixture. For this study, I use spot prices for the Europe Brent oil quoted in United States dollars to examine the effect of world oil prices on the Russian Stock index volatility. The data for oil prices was obtained through the United States Energy Information Administration website. Brent oil was chosen as a world oil indicator for this study because Russia uses the Brent oil price as a basis for price estimation of Russian oil and the data are consistent over time. Even though the Russian Export Blend Crude Oil (REBCO) started to be quoted in New York Mercantile Exchange (NYMEX) in October of 2006, it has significant limitations. First, not all brands of Russian oil are included in REBCO. Second, only a limited number of ports of embarkation release REBCO for shipment. And third, the timespan of the REBCO data is insufficient for this research.

The use of Brent oil spot prices applied in this paper is justified by the pricing settings in international markets for different Russian blends of oil. Most of the Russian oil is traded under the contracts consigned by either oil companies directly or oil traders. Most of the Russian oil is sold to European customers. In this regard Brent oil is a role model and the price-setting basis for the oil that has been exported and/or imported to Europe. Even though oil exchanges help to designate major price points, the major pricing factor for the Russian oil is still over-the-counter demand and supply orders from major players. For analytical reasons, some research companies based on available price information determine value differentials in regard with the Brent oil price to calculate the consensus value for the Russian blends.

The Russian Trading System (RTS) Index is used to represent the Russian stock market. The RTS Index is one of the leading indicators of the stock market activity in Russia and since its inception in 1995 has been using the United States Dollars to calculate the value of the index. The index is capitalization-weighted, with free-float coefficients. There are 50 preferred and common shares forming the index's basis, and the index is calculated every 15 seconds during the trading session (MICEX-RTS 2012b).

The RTS Index and market capitalization are calculated by the following formulas (MICEX-RTS 2012a):

$$I_n = Z_n * I_1 * \frac{MC_n}{MC_1} \tag{3.1}$$

In the equation 3.1 I_1 is an initial value of the Index, MC_n and MC_1 represent the sum of the stock market capitalizations in USD, Z_n – correcting coefficient.

$$MC_n = \sum_{i=1}^{N} W_i * P_i * Q_i * C_i \tag{3.2}$$

In the equation 3.2 W_i is the correcting free-float coefficient for the i-th security, C_i designates the coefficient restricting the capitalization weight of the ith security, Q_i represents the number of shares of the ith type issued by the issuer as of current date, P_i is the price of the i-th security in US dollars as of time t, and N denotes the number of stocks (RTS Index constituents).

To examine the volatility of the Russian stock market returns and its dependency on world's oil prices, I used weekly data for the oil prices and stock market index. The weekly data is calculated by transforming daily spot Brent oil prices through average methodology in Eviews 7.0 Software package.

In this study, I use weekly data over the period from September 1, 1995 to June 1, 2012. The period starts with the date of the RTS Index inception and continues up-to date allowing examination of the volatility of the Russian stock market returns movements and related explanatory factors. The weekly data were chosen to provide thorough evaluation of oil and stock prices dependency and to assess the variance residuals. Since the Russian stock market is highly volatile, the weekly data will provide better results in estimating the degree of influence of the oil market on the Russian stocks' returns, eliminating daily "noise" fluctuations, since the oil price movements have a relatively long-term effect on the stock market. Also, using weekly data can eliminate the world oil and the Russian stock market time differences factor brought by the use of high frequency data that could have influenced the determination of the price dependencies. In addition, the weekly data in comparison to the daily one helps to smooth the values due to fewer non- synchronous trading sessions and make the data more consistent over the long period of time.

In the econometric model and in the associated analysis, I apply logarithmic returns of the Brent oil prices and the RTS Index values to evaluate the significance of their volatility interdependency. The formula for the logarithmic weekly return calculation for both variables is as follows:

$$Log\ return_i = Log(X_i) - Log(X_{i-1}) \tag{3.3}$$

The time series of the oil and index data are synchronous in this study, meaning that the prices are obtained at closing and adjusted only for those dates that have information on both variables.

3.2. Unit Root Test

In econometrics, a unit root test is a mechanism that checks whether autocovariances depend on time. In time series data, this feature is important because if the data are not stationary, i.e. the data have a unit root, it may cause misinterpretations in statistical inferences. When estimation of slope coefficients are performed through the ordinary least squares (OLS) methodology, the data for the analysis should be stationary; otherwise, the model may provide invalid estimates. There are several tests that examine whether the data used in the model are stationary or not, such as the Augmented Dickey–Fuller (ADF) test, Dickey–Fuller test, The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) Test, The Phillips-Perron (PP) Test and Elliot, Rothenberg, and Stock Point Optimal (ERS) Test (Quantitative Micro Software 2012b, 387).

In time-series modeling research papers and many econometric commentaries, such as Ayat and Burridge (2000), the ADF is the most popular method of testing the presence of the unit root in a model. For my research I have also chosen to perform the ADF test developed by Dickey and Fuller (1979), because this model is more appropriate to provide good estimates for the large sets of time series data. The test is conducted using the following equations (Vošvrda 2012, 5):

$$\Delta Y_t = \varphi_0 + \textstyle\sum_{i=1}^{k} \alpha Y_{t-1} + X_t + \epsilon_t \qquad (3.4)$$

$$\Delta Y_t = \varphi_0 + \varphi_1 T + \textstyle\sum_{i=1}^{k} \alpha Y_{t-1} + X_t + \epsilon_t \qquad (3.5)$$

$$\Delta Y_t = \textstyle\sum_{i=1}^{k} \alpha Y_{t-1} + X_t + \epsilon_t \qquad (3.6)$$

Equation 3.4 describes the ADF test for a unit root with an intercept or drift; equation 3.5 describes the ADF test for a unit root with a drift and deterministic time trend; equation 3.6 describes the ADF test for a unit root without an intercept and a trend. In the equations Δ is the first difference operator; t is the time period; k represents the number of lags and ϵ is the error term; φ and α are parameters. The null hypothesis (H_0) is that the time series Y_t has a unit root and is not stationary and H_0 can be rejected if p-value is less than the certain level of significance or the absolute value of t-statistic is more than the absolute value of the level of significance.

Lagged difference terms are chosen in order to remove the serial correlation in the residuals in order to diminish the influence on the model of the growing error component and effect of the increasing variance. The increasing number of lags in the model decreases the effective sample, and lowers the degree of freedom, while the estimated parameters are increased, leading to the loss of power in the model (Wolters and Hassler 2006, 46).

The effect of the growing residual errors can be significant and result-changing when the regression model is run. The error component for the model is accumulated when several variables experience unity in their coefficients, and the results on t-statistics and R-squares may be misleading, providing wrong conclusions.

Another important factor in testing for the unit root in the model that influences the unit root test results is the inclusion of exogenous variables in the regression, i.e. to run the unit root test with an intercept; an intercept and a linear time trend; or with no intercept and no time trend. "Including too many of these deterministic regressors results in lost power, whereas not including enough of them biases the test in favor of the unit-root null….inclusion of an intercept, or an intercept and a time trend, is necessary to allow representation of the alternative hypothesis competing against the null of a unit root" (Elder and Kennedy 2001, 138).

If the data series are not stationary, the application of first difference approach is justified to make the data stationary and conduct further analysis utilizing regression-based approaches, ARMA and ARCH models.

3.3. Johansen Cointegration Test

When the data are stationary, a test on long-run association or cointegration can be performed to investigate whether variables follow a common stochastic movement. Cointegration represented by two time series in this paper is examined by the Johansen Cointegration Test. It is a Vector Autoregression (VAR)-based cointegration test designed by Johansen (1991). Johansen's methodology uses the VAR of order p to establish the association given by the following equation (Quantitative Micro Software 2012b, 685):

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + BX_t + \epsilon_t \tag{3.7}$$

In this equation Y_t is a k-vector of non-stationary I (1) variables, X_t is a d-vector of deterministic variables, and ϵ_t is a vector of innovations.

The null hypothesis in the Johansen Cointegration Test is that there is no cointegration equations or long-run association between variables and H_0 is tested by comparing p-value with certain level of significance. This means that there are no cointegrated components of Y_t, and they equal zero. The number of cointegration relations is determined until the sequential null hypothesis is rejected.

Since the Johansen Cointegration test uses VAR-based methodology and the values of A are determined by the number cointegrating vectors, the maximum likelihood estimator has to be defined using the trace test or the maximum eigenvalue.

The trace test examine "the null hypothesis of r cointegrating vectors against the alternative hypothesis of k cointegrating relations, where k is the number of endogenous variables, for r = 0, 1,…, k – 1. The alternative of k cointegrating relations corresponds to the case where none of the series has a unit root and a stationary VAR may be specified in terms of the levels of all the series" (690). The trace statistic is computed with the following formula (690):

$$LR_{tr}(r|k) = -T\sum_{i=r+1}^{k}(1- \gamma_i) \tag{3.8}$$

In the equation 3.8 γ_i is the i-th largest eigenvalue.

Another approach to determine the number of cointegrating vectors is to use the maximum eigenvalue statistic which tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of (r + 1) cointegrating vectors (Hjalmarsson and Osterholm 2007, 5). This test statistic is computed as (Quantitative Micro Software 2012b, 690):

$$LR_{max}(r|r+1) = -T\sum_{i=r+1}^{k}(1- \gamma_i) = LR_{tr}(r|k) - LR_{tr}(r+1|k) \tag{3.9}$$

The equation 3.9 is computed for r = 0, 1, …, k – 1.

Johansen and Juselius (1990) argue that the trace statistic and the maximum eigenvalue statistic may generate contradictory outputs for different cointegrating vectors. Also, the Johansen Cointegration Test checks the model on the long-run association, assuming that the relationship remains constant during the period of study. But since the economy develops over time through technological and structural transformations responding to accommodate external shocks, the association between variables can hardly be consistent over the long period of time.

3.4. Granger causality test

Even though the cointegration test determines association between variables, it does not establish causality links; neither does a correlation analysis. The causal relationship between variables based on precedent association was developed by Granger (1969).

The Granger methodology determines how much one stationary variable is explained by past variations and how the explanatory results can be improved if another stationary variable's lagged values are added into the model. “It is important to note that the statement x Granger causes y does not imply that is the effect or the result of x. Granger causality measures precedence and information content but does not by itself indicate causality in the more common use of the term” (Quantitative Micro Software 2012a, 428). This built-in assumption has an influence on the dual dependency of the variables, meaning that if one variable has a Granger-cause on another variable, the result will not necessarily have an effect on the vice versa relationship.

The Granger causality concept is built on the assumption that the effect is followed by the cause of the variables relationship influencing a feedback stochastic process.

The mathematical framework of the model is based on the linear modeling of stochastic processes. In this paper I used the bivariate linear autoregressive model of two variables Y and X (429):

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_l y_{t-l} + \beta_1 x_{t-1} + \cdots + \beta_l x_{-l} + \epsilon_t \tag{3.10}$$

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_l x_{t-l} + \beta_1 y_{t-1} + \cdots + \beta_l y_{-l} + u_t \tag{3.11}$$

In this stochastic model, α and β are the coefficients of the model meaning the contributions of each lagged observation to the forecasted values $y_t$for the equation 3.10 and x_t for the equation 3.11; and $\epsilon_t$and u_t are residuals or prediction errors for each time series dataset.

The null hypothesis in this model is that x does not cause y in the first regression and y that does not cause x in the second regression.

One of the crucial parameters for the data to fit into the model well and generate significant results is the determination of the number of lags in regression for the Granger Causality Testing procedure. The number of lags is crucial and has result-changing consequences. It is assumed that it is more appropriate to select more rather than fewer lags, because in that case the mathematical framework of the regression is based on the significance of all past information; a lag length in this case should correspond to the principle of time association over which one variable could have a forecasting power for the other variable (428).

The Granger causality framework estimates the direction of the linkages between variables assuming predominantly linear signals and stationary time series data. If data are non-stationary, the test is performed with first difference results of the variables.

3.5. General Autoregressive conditional heteroscedasticity (GARCH) model

It has been observed that the volatility of a time series data is normally not constant (Library Economics Liberty 2012). The periods of high volatility and the periods of low volatility can be observed through the degree of fluctuations of the variable's residuals. In analysis of volatilities and forecasting conditional variances it became a standard to apply different forms of General Autoregressive conditional heteroscedasticity (GARCH) models, which assume that the variances of error terms are not equal (Engle 2001, 157). ARCH models were first presented by Engle in 1982 and Generalized ARCH (GARCH) by Bollerslev in 1986.

ARCH family models define autoregressive heteroscedasticity through the use of conditional maximum likelihood approach, in which "conditional likelihood" refers to probability that is computed based on estimated values for the squared residuals and variances prior to the estimation sample (STATA Press 2011, 25). The term "heteroscedasticity" refers to a non-constant volatility behavior of a variable's variance over a time period. In the standard linear regression models, in which the estimation of coefficients use the least squares methodology, the variance of the residuals is constant, meaning that it is homoscedastic.

The model uses past information of the variable's behavior to project the conditional mean and variance of the variable. The uniqueness of the ARCH models is the inclusion of past variance into the equation to predict future values of the variable. Previous prediction models used approaches that mostly concentrated on the mean values, and they could not incorporate the degree of fluctuations of the variables into the forecasting methodology.

ARCH model that was developed by Engle (1982) is represented as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 \tag{3.12}$$

In the equation 3.12 α represents coefficients and a is a residual return to forecast a conditional variance for future periods.

The ARCH models mathematical framework is based on the conditional normality principle, and in time-varying samples, this may lead to fat tails and the mixture of normal (Reider 2009).

In GARCH models, the residuals behavior or error terms behavior is called conditionally heteroscedastic if the periods of high volatility are followed by the periods of high volatility and the periods of low volatility are followed by the periods of low volatility. "The variance of the dependent variable is modeled as a function of past values of the dependent variable and independent or exogenous variables" (Quantitative Micro Software 2012b, 197). The sample size of observations has to be large enough in order to reduce the inconsistency effect of the error terms due to heteroscedasticity of the model.

GARCH (p, q) model effectively assesses important features of economic data when the volatility of the residuals is grouped in the sequential periods of time and also in case of returns behavior forming thick tails, as it was first described by Mandelbrot (1963): ". . . large changes tend to be followed by large changes of either sign, and small changes tend to be followed by small changes" (394).

GARCH models are calculated on the assumption that the weights of the past variances are not equal and do not have the same effect on the future variance, compared to the ARCH models. Even though the weight of the variances in the model decline as the lag grows, it never reaches zero, meaning that even the first values in the sample add deviation effect into the future movements.

The GARCH model also has some limitations that constrain the use of the model in the cases of unmatched and small sample data. In order to provide reliable results for the volatility forecasting the sample should be relatively big and consistent in time and gaps with exogenous variables to achieve stability of the sample.

In this paper I use GARCH (1, 1) methodological framework to estimate the stochastic process of the Russian stock market returns with respect to the movements of world oil prices. The first number in the parenthesis (1, 1), when the GARCH model is described, refers to the number of autoregressive lags, or ARCH terms, in the equation, and the second number specifies the number of moving average lags, or GARCH terms (Engle 2001, 160). In many cases, the standard GARCH (1, 1) model is used to assess volatility, but sometimes the higher lag values are required to provide reliable variance forecasts. "The GARCH (1, 1) is the simplest and most robust of the family of volatility models. However, the model can be extended and modified in many ways" (166).

$$Y_t = C_1 + C_2X_2 + \epsilon_t \tag{3.13}$$

$$\sigma_t^2 = C_3 + C_4\sigma_{t-1}^2 + C_5e_{t-1}^2 \tag{3.14}$$

The GARCH (1,1) model consists of two equations: the first one is a mean equation (3.13) written as a function of an exogenous variable with associated error term, and the second one is a variance equation (3.14) written as a function of previous conditional variances. The conditional variance equation is represented by three terms (Quantitative Micro Software, 2012, 198): a constant term C_3; volatility from the previous period, measured as the lag of squared residual from the mean equation: e_{t-1}^2 (ARCH term); and the last period's forecast variance: σ_{t-1}^2 (GARCH term).

The application of the GARCH models is to determine what characteristics, factors and variables affect the future volatility of an estimated variable through the mechanism of comparing a p-value with designated levels of significance to make a conclusion whether to reject a null hypothesis (whereby an element does not have influence on the variable's volatility).

Time-series modeling involves not only a model definition (e.g. GARCH model), but also a parameters estimation. After the model is selected, it is necessary to quantify parameters to make the model best suited for the specific case. The number of lags or the order of a model plays a central role to fit the time-series data into the regression equation. "The model can be forced to fit the data increasingly well by increasing its order. However, as is well known, the fact that the fit set errors are small is no guarantee that the prediction set errors will be. Many of the terms in a complex model may simply be accounting for noise in the data" (Koehler and Murphree 1988, 187).

In this work the number of optimal lags observations (appropriate model order) was determined through the Akaike Information criterion (AIC) (1974) and the Schwarz Information criterion (SIC) (1978).

Both AIC and SIC tests are based on the maximum likelihood-based models, that are asymptotically effective and unbiased, the tests provide accurate results in the cases of 30 or more observations in the sample.

AIC is computed by the following formula:

$$AIC = -\frac{2l}{T} + 2k/T \tag{3.15}$$

SIC is computed as:

$$SIC = -\frac{2l}{T} + (klogT)/T \tag{3.16}$$

In the equations 3.15 and 3.16 l represents a log likelihood function (assuming normally distributed errors) calculated using the estimated values of the coefficients, k is the number of parameters in the model, and T designates the number of observations in the sample.

l, log likelihood function is calculated as:

$$l = -\frac{T}{2}(1 + \log(2\pi) + \log\left(\frac{\widehat{\epsilon'}\hat{\epsilon}}{T}\right)) \tag{3.17}$$

The AIC and the SIC differ in the treatment of penalty associated with the number of parameters in the model, but both are considered objective criteria to measure the sustainability of the model in regard to the maximum-likelihood concept.

It is common to use the maximum likelihood estimation to forecast ARCH results in order to determine the distribution values for innovations in the log-likelihood function. The results from the GARCH (1, 1) model may be biased by the error distribution technique applied in the model. In order to examine the consistency of the results, I generated outcomes of the GARCH (1, 1) model using Normal (Gaussian), Student's t and Generalized error distribution methodologies applying the following formulas (Angelidis, Benos and Degiannakis 2010, 4):

1. Normal Gaussian Distribution of standardized innovations:

$$L_T\,|\big(\{y_y\};\theta\big) = -\frac{1}{2}\,[Tln(2\pi) + \sum_{t=1}^{T} z_t^2 + \sum_{t=1}^{T} \ln(\sigma_t^2)] \tag{3.18}$$

2. T-distributed innovations:

$$L_T(\{y_t\};\ \theta) = T\ \left[\ln\Gamma\left(\frac{v+1}{2}\right) - \ln\Gamma\left(\frac{v}{2}\right) - \frac{1}{2}\ln[\pi(v-2)]\right] -$$

$$\frac{1}{2}\sum_{t=1}^{T}[\ln(\sigma_t^2) + (1+\ \ v)\ln(\ 1+\ z_t^2/(v-2)] \tag{3.19}$$

3. Generalized normal distribution (GED) innovations:

$$L_T\ (\{y_t\};\ \theta) = \sum_{t=1}^{T}[ln\left(\frac{v}{\lambda}\right) - \frac{1}{2\left|\frac{z_t}{\lambda}\right|} - (1+\ v^{-1})ln(2) - ln\Gamma\left(\frac{1}{v}\right) - \frac{1}{2ln(\sigma_t^2)}] \tag{3.20}$$

In the equations 3.18, 3.19, 3.20 θ is the vector of the parameters estimated to calculate the variance and density function; z_t represents identically distributed standardized innovations; Γ(v) is a label for the gamma function; v is the tail-thickness parameter.

The results of the volatility forecasting GARCH-type models can significantly help financial agents to predict future volatility of an asset in the long-term establishing a projected variance from the last periods’ deviations (GARCH term), and mean values from previous period (ARCH term) (Quantitative Micro Software 2012, 196). The models help to assign and, later, make necessary adjustments of the variance values (in response to bigger than normal previous movements) into financial programs and, especially, portfolio management systems.

4. Research Results

4.1. Summary Statistics

The descriptive statistics of logarithmic returns of the oil price and the RTS Index values are presented in the table 4.1 to analyze the basic characteristics of the data series. The means and standard deviations of the variables are computed in annual terms (weekly value multiplied by 52 and the square root of 52, respectively).

Table 4.1: Summary statistics

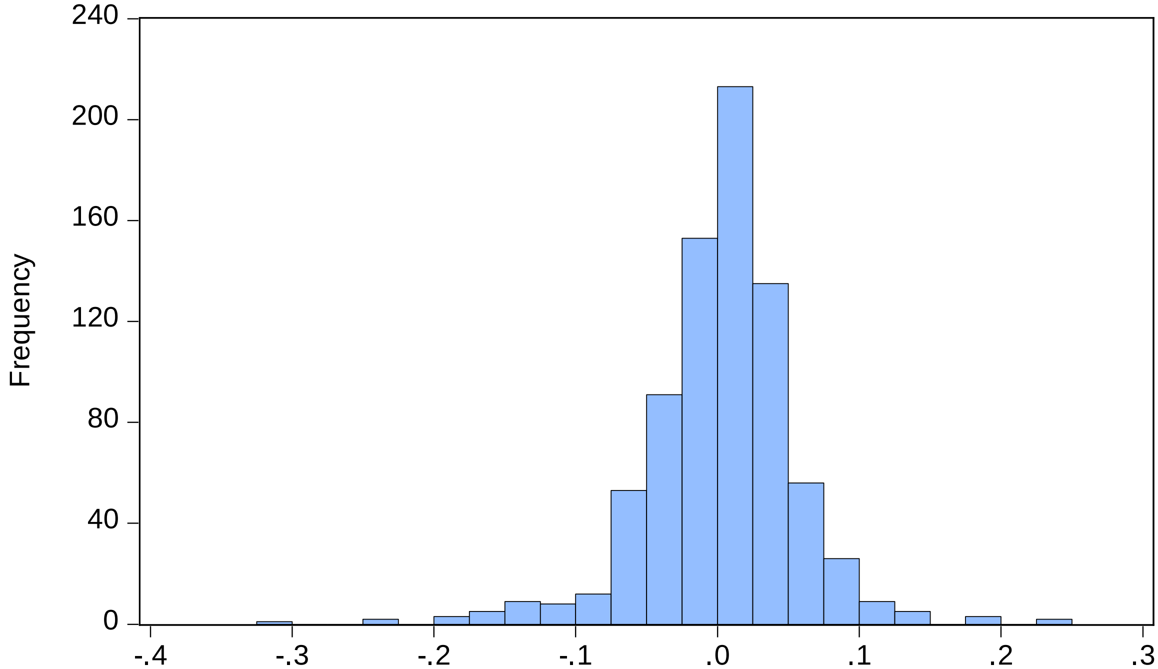
	Mean (%)*	Median	Max	Min	Std. Dev. (%)*	Skewness	Kurtosis	Jarque-Bera	Prob.	Obs.
RTS	9.68	0.0049	0.1668	-0.2305	30.79	-0.5510	4.7056	135.05	0.00	786
Oil Price	16.07	0.0081	0.2499	-0.3152	39.15	-0.5642	7.4408	687.58	0.00	786

* Means and standard deviations are represented in annual terms

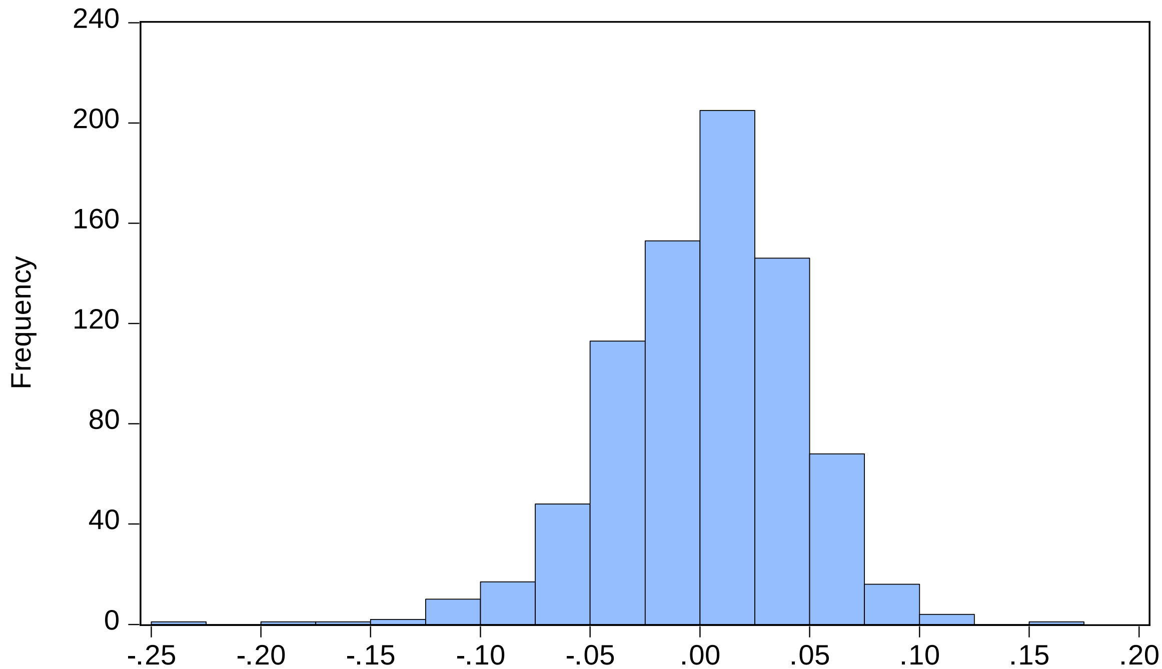
For each variable the means are significantly smaller than associated standard deviations in absolute values. The Index Value series have a kurtosis of 4.7056 that is more than a normal probability distribution value of 3, meaning that the distribution has a sharper peak and fatter tails. For the oil price values, the kurtosis shows the value of 7.4408 which brings a higher value than for the Index's kurtosis. The distribution of the oil price returns has a positive excess kurtosis (or leptokurtic) translating into sharp peak, and heavy and long tails. High levels of kurtosis for the both variables' data sets are the consequences of high inconsistent volatility of the variances during the time period.

Both data series provide negative skewness results (Picture 4.1 and Picture 4.2), where distributions are skewed to the left side of the probability density function, indicating that the means lie to the left of both the modes and medians.

Picture 4.1: Distribution of the RTS Index logarithmic returns



Picture 4.2: Distribution of the Brent Oil logarithmic returns



The goodness of fit test, or the Jarque–Bera test, also examines how well the probability values are distributed in regard to the normal distribution model, and it is measured through "the difference of the skewness and kurtosis of the series with those from the normal distribution" (Quantitative Micro Software 2012a, 318). It is computed by the following formula:

$$JB = \frac{N}{6}\left(S^2 + \frac{(k-3)^2}{4}\right) \tag{4.1}$$

In the equation 4.1 S is a skewness and k is kurtosis.

Kurtosis, skewness statistics results and the Jarque-Bera test and its corresponding p-values provide sufficient evidence that both variables' time-series data sets do not follow normal distribution, then the Null hypothesis: "the data is normally distributed" is rejected for both variables, meaning that the determination of whether the data is stationary are required.

The oil price returns have a bigger range in values than the index returns in absolute values distribution meaning that the amplitude of growth was higher for the oil price weekly returns.

Table 4.2: OLS Regression model

Dependent Variable: RTS Index				
Method: Least Squares				
Sample: 9/08/1995 6/01/2012				
Included observations: 786				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	-110.8021	19.45928	-5.694048	0.0000
Brent oil price	19.04384	0.318899	59.71743	0.0000
R-squared	0.819777	Mean dependent var		869.3795
Adjusted R-squared	0.819547	S.D. dependent var		689.8443
S.E. of regression	293.0439	Durbin-Watson stat		0.022936
Sum squared resid	67325809	F-statistic		3566.171
Log likelihood	-5579.018	Prob(F-statistic)		0.000000

Also by examining weekly dynamics of the RTS Index and Brent oil price, the variables are positively correlated and the explanatory power represented by R-squared equals 0.819, meaning that the RTS Index value movements can be explained by 81.9% by the Brent oil prices.

4.2. Unit Root test results

Examination of conditional volatility between variables requires all data t be stationary, which means variances and means of variables' time series data should not change over time or position. One of the most popular and effective approach to investigate whether the data are stationary is Augmented Dickey-Fuller (ADF) Unit root test. In table 4.3 and table 4.4, combined results of the ADF test for the weekly RTS Index logarithmic returns and the weekly Brent oil logarithmic returns are presented.

Table 4.3: Augmented Dickey-Fuller (ADF) test statistic (RTS Index Values)

	Intercept Only	Intercept and trend	None
	t-statistic (p-value)	t-statistic (p-value)	t-statistic (p-value)
ADF	-20.72505 (0.0000)	-20.74405 (0.0000)	-20.68412 (0.0000)
Critical Values			
1%	-3.438454	-3.969785	-2.567911
5%	-2.865007	-3.415551	-1.941227
10%	-2.568671	-3.130011	-1.616428
Coefficient	-0.708705	-0.710063	-0.706276

Table 4.4: Augmented Dickey-Fuller (ADF) test statistic (Oil Prices)

	Intercept Only	Intercept and trend	None
	t-statistic (p-value)	t-statistic (p-value)	t-statistic (p-value)
ADF	-22.29176 (0.0000)	-22.28056 (0.0000)	-22.27364 (0.0001)
Critical Values			
1%	-3.438454	-3.969785	-2.567911
5%	-2.865007	-3.415551	-1.941227
10%	-2.568671	-3.130011	-1.616428
Coefficient	-0.778329	-0.778427	-0.776825

ADF Test designates that there is no presence of the autoregressive unit root for both RTS Index returns and Brent oil returns. The null hypotheses ($H_0: variable\ has\ a\ unit\ root$) of both variables are rejected for all trend cases using ADF Test and the alternative hypotheses (H_1: *variable has a stationary data*) are accepted.

The ADF t-statistic to test the Null Hypotheses is computed by utilizing 3 scenarios: with a constant (intercept) only, with a constant and a trend, without a constant and a trend. ADF test t-statistic when only intercept is included in the test equation for the RTS Index weekly returns equal to -20.72505 which is higher than 1%, 5%, 10% critical values in absolute terms and with a p-value of 0.0000, which is less than 1%, 5%, 10% levels of significance as well. Also the coefficient of the 1 day lagged daily returns is negative, which means that the results are significant. ADF test t-statistic when a constant and a trend are applied and when none exogenous variables is present provides significant results of -20.74405 and -20.68412 respectively that reject Null hypotheses at 1%, 5% and 10%. Coefficients of the different equations in regard with trend statistics are all negative in the RTS Index weekly logarithmic returns. Combined results provide sufficient evidence that the data for the weekly RTS Index returns are stationary.

Since the volatility analysis requires all time series data to be stationary, the ADF test was performed to check whether the Brent oil weekly logarithmic returns data is stationary. ADF test t-statistic and corresponding p-values of weekly oil returns under the 3 trend cases (a constant only, a constant and a trend, no constant and no trend) are provided respectively as follows: -22.29176 with p-value of 0.0000, -22.28056 with p-value of 0.0000, and -22.27364 with p-value of 0.0000. All 3 coefficients for the different trend equations are negative. The results conclude that the weekly oil logarithmic returns data is stationary and significant.

4.3. Johansen Cointegration test results

Cointegration between the RTS weekly Index logarithmic returns and the Brent oil prices weekly logarithmic returns is tested by the Johansen Cointegration Test. In the table 4.5, the summary of the Unrestricted Cointegration Rank Test (Trace) and Unrestricted Cointegration Rank Test (Maximum Eigenvalue) is presented under the assumption that the data of both variables have “no trend” behavior and the cointegrating equations have only intercepts. This assumption is justified by the “non-zero” mean values the variables have and the deterministic terms are common inside cointegrating equations (error correction terms).

The result of the Johansen sequential Testing procedure using Unrestricted Cointegration Rank Test (trace statistic technique) is that the null hypothesis ($H_{0,1}$: *there is no cointegration between variables)* should be rejected since p-value is 0.0001 and is less than 5% level of significance meaning there is a long-run association between the RTS Index logarithmic returns and the Brent oil logarithmic returns. The same results are obtained when the Maximum Eigenvalue statistic is run. The p-value of Eigenvalue testing that there is a cointegration ($H_{0,2}$)) is 0.0001 and the null hypothesis should be rejected.

Table 4.5: Johansen Cointegration Test

Hypothesized # of CEs	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
Unrestricted Cointegration Rank Test (Trace)				
None * ($H_{0,1}$)	0.289177	511.5495	12.32090	0.0001
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
None * ($H_{0,2}$)	0.289177	267.6043	11.22480	0.0001

* denotes rejection of the hypothesis at the 0.05 level

Table 4.6: Optimal Lag length testing

VAR Lag Order Selection Criteria						
Endogenous variables: LogRet(RTS) LogRet(Oil)						
Exogenous variables: C						
Date: 08/23/12 Time: 14:09						
Sample: 9/08/1995 6/01/2012						
Included observations: 778						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	2571.999	NA	4.63e-06	-6.606680	-6.594709	-6.602076
1	2622.723	101.0584	4.11e-06*	-6.726796*	-6.690882*	-6.712981*
2	2624.061	2.657157	4.14e-06	-6.719950	-6.660095	-6.696926
3	2629.532	10.84461	4.12e-06	-6.723733	-6.639936	-6.691500
4	2632.405	5.678394	4.13e-06	-6.720834	-6.613095	-6.679391
5	2633.210	1.587784	4.17e-06	-6.712622	-6.580941	-6.661969
6	2638.940	11.26784*	4.15e-06	-6.717068	-6.561445	-6.657206
7	2639.647	1.387062	4.18e-06	-6.708603	-6.529038	-6.639532
8	2641.858	4.325654	4.20e-06	-6.704005	-6.500497	-6.625724

* indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

It is also important to specify the number of lags of the VAR test for cointegration analysis. To determine the optimal lag length for the Johansen Cointegration Test I used VAR lag order selection criteria function in Eviews 7.0. The results (presented in the table 4.6) show that 1 lag for the variables in the regression is optimal according to the Akaike Information criterion with a maximum absolute value of - 6.726796, the Schwarz Information criterion with a maximum absolute value of - 6.690882, also the Final Prediction error approach and the Hannan-Quinn information criterion show the optimality of Lag 1 with respective values of 4.11e-06 and -6.712981.

4.4. Granger Causality test results

Even though the Johansen Cointegration Test establishes long-run association between variables, it does not determine the causality links between them. The Granger Causality Test helps to identify any directional interconnection between the RTS Index weekly logarithmic returns and the Brent oil weekly logarithmic returns utilizing stationary covariance data. Previously, the Augmented Dickey-Fuller Test showed that the data are stationary and the optimal number of lags was chosen based on the Akaike Information criterion, the Schwarz Information criterion, the Hannan-Quinn information criterion and the Final Prediction error method. All 4 criteria identify the lag 1 as an optimal to perform analysis with the data.

Table 4.7: Granger Causality Test

Null Hypothesis*:	Obs	F-Statistic	Prob.
Lag: 1			
$H_{0,1}$ Brent oil returns do not Granger Cause RTS Index returns	785	1.58746	0.0234
$H_{0,2}$ RTS Index returns do not Granger Cause Brent oil returns		1.15116	0.2637
Lag: 2			
$H_{0,1}$ Brent oil returns do not Granger Cause RTS Index returns	784	1.58729	0.0220
$H_{0,2}$ RTS Index returns do not Granger Cause Brent oil returns		1.17069	0.2396
Lag: 3			
$H_{0,1}$ Brent oil returns do not Granger Cause RTS Index returns	783	1.54279	0.0279
$H_{0,2}$ RTS Index returns do not Granger Cause Brent oil returns		1.16219	0.2466
Lag: 4			
$H_{0,1}$ Brent oil returns do not Granger Cause RTS Index returns	782	1.48968	0.0378
$H_{0,2}$ RTS Index returns do not Granger Cause Brent oil returns		1.19271	0.2113
Lag: 5			
$H_{0,1}$ Brent oil returns do not Granger Cause RTS Index returns	781	1.48905	0.0362
$H_{0,2}$ RTS Index returns do not Granger Cause Brent oil returns		1.20554	0.1958

*5% Level of Significance

The values of F statistic suggest that the Brent oil logarithmic returns Granger-cause the RTS Index logarithmic returns, and at the same time the RTS Index logarithmic returns do not cause the Brent oil logarithmic returns. This conclusion is based on p-value of 0.0234 generated by testing the first null hypothesis ($H_{0,1}$: *Brent oil returns do not Granger Cause RTS Index returns*) and $H_{0,1}$ can be rejected using the 5% level of significance and 1 lag in the model. At the same time, the second null hypothesis ($H_{0,2}$: RTS Index returns do not Granger Cause Brent oil returns) cannot be rejected with associated p-value of 0.2637 for the 5% level of significance. Also since the Granger Causality Test is very sensitive to the applied numbers of lags in the regression, I have tested the relationship using different number of lags. All extra results tested for the lags 2, 3, 4, and 5 provide a similar conclusion that the Brent oil returns cause the RTS Index returns, but not vice versa.

The Granger Causality Test suggest that the past values of the Brent oil returns contribute to the prediction of the present value of the RTS Index returns together with the past values of the RTS Index return values. Moreover, by the single regressions it can be showed that in this case a small change in the number of lags does not lead to the change in results of the Granger causality test, which provides sufficient grounds together with deviation of F-statistic to conclude that the application of the results is significant.

4.5. GARCH: Empirical Results:

4.5.1. The Brent Oil and the RTS Index movements

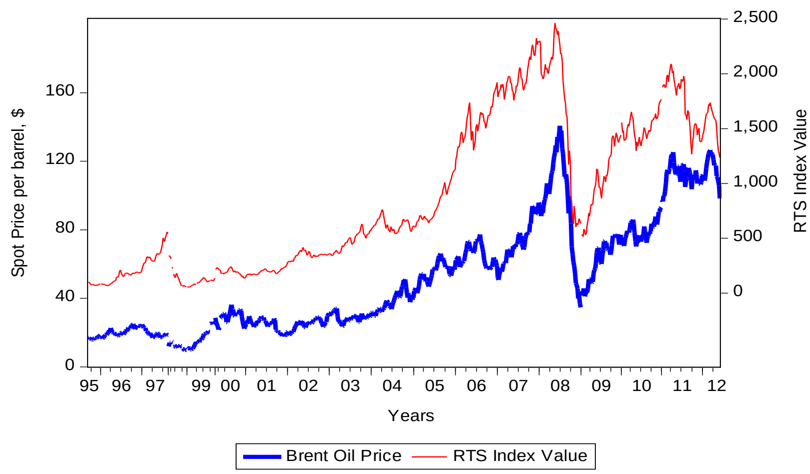
The initial weekly data for the Brent Oil prices and the RTS Index values have been plotted together on the graph to examine the co-movement and establish the possible relationship between variables. For the timespan of 17 years covered in this research, there has been a very strong positive correlation between 2 variables with R-squared value of 81.9%. Even though during the most of the time period, the movements are positive; there have also been several periods of divergence in the data sets.

The variables' returns dynamics are presented in the Picture 4.3. It is clear that the Russian stock market does not move along with the world oil market all the time. For instance, in 1996 and the beginning of 1997, when oil prices were going constantly downward, the Russian stock market skyrocketed, reaching the maximum level at that time of 570, translating it into 570% in absolute returns since the September 1995, when it first was quoted. The effect of oil prices on the whole index at that time was less significant, while other factors such as benchmark valuation had a bigger weight. Most of the companies were underestimated significantly by the comparative companies abroad, which made the Russian enterprises very appealing to the foreign investors, even at the time, when oil prices started to decline.

The sharp decline in the Russian stock market in late 1997 was due to the Asian financial crisis; due to the 1998 the Russian financial crisis, the government had to default on its debt, and both events hit the RTS Index significantly.

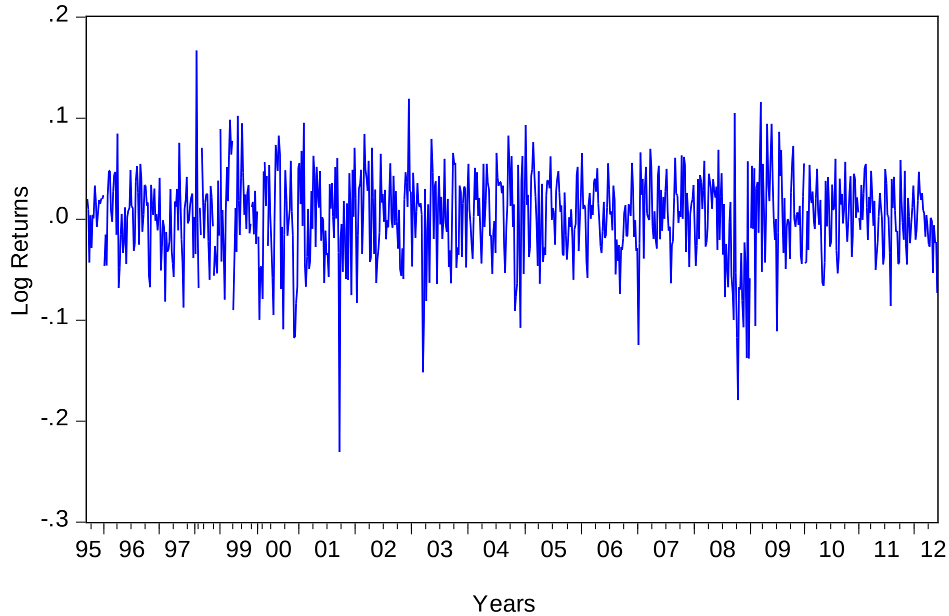
During the 2000s the dependency of the Russian economy on oil and gas revenues has been increasing, and the fuel-energy companies grew in assets, significantly occupying the biggest share of the index capitalization. Even though the degree of the movements between the oil price and the RTS index value is not consistent over the whole period, the directional relationship is very strong and the index reflects relatively fast to the price changes in the oil market.

Picture 4.3: Dynamics of the weekly Brent oil price and the weekly RTS Index value



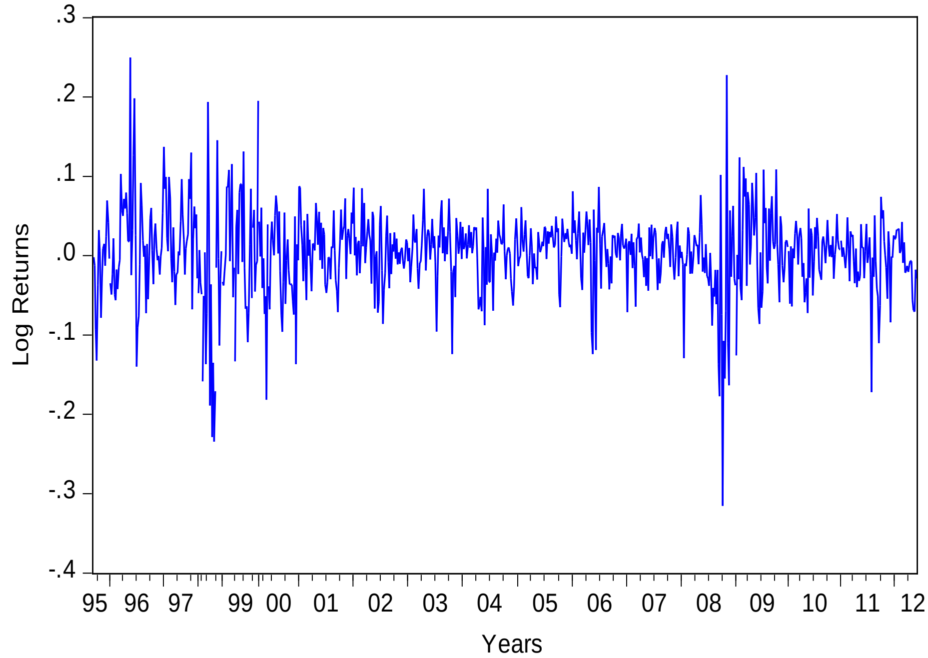
The GARCH model is applied to analyze the volatility transmission between the Brent oil weekly logarithmic returns and the RTS Index weekly logarithmic returns because the data of both variables in the Pictures 4.4 and 4.5 show the tendency of returns movements, in which past returns have an effect on the future values. In the Brent oil data, the returns were highly volatile between 1997 and 2003, but after 2003 and till the World Economic and Financial crisis of 2008 the logarithmic returns on the Brent oil showed less volatility.

Picture 4.4: Brent Oil Weekly Logarithmic Returns



The use of the GARCH model is also valid for the RTS Index data set: from 1995 till 2000 it was a period of high volatility of the Russian stock market, in which high past movements had been taken into future returns; on the contrary, after 2000 and till 2008 the market was relatively stable without high sudden return movements, proving that the low volatility also points to low volatility in the future.

Picture 4.5: RTS Index Weekly Logarithmic Returns



4.5.2. Implications of the GARCH Model

The GARCH (1, 1) model examines the volatility transmission between the Brent oil market and the Russian stock market returns. Through the GARCH (1, 1) model I investigated the explanatory factors of RTS Index returns volatility and tested the Brent oil returns' influence on the fluctuations of the stock market. One-period lagged Brent oil returns (ARCH (1) parameter) affect significantly in the following distribution cases: Normal distribution, Student's t distribution, Generalized error distribution (GED) in the conditional return-generating process. These results are consistent with the findings of oil fluctuations and European stock markets showing the strong volatility influence of the oil market in the work of Arouri, Jouini and Nguyen (2012).

Table 4.8: Output of the GARCH Model

Dependent Variable: RTS Index Log Returns				
Method: ML - ARCH (Marquardt)				
Sample (adjusted): 9/05/1995 6/05/2012				
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)				
Normal Distribution				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.003891	0.001423	2.734136	0.0063
RLOGBP	0.377757	0.033012	11.44295	0.0000
Variance Equation				
C	8.32E-05	1.66E-05	5.001311	0.0000
RESID(-1)^2	0.164771	0.025712	6.408233	0.0000
GARCH(-1)	0.807321	0.025018	32.27002	0.0000
Student's t distribution				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.005258	0.001253	4.197126	0.0000
RLOGBP	0.340835	0.029789	11.44154	0.0000
Variance Equation				
C	7.40E-05	3.00E-05	2.462144	0.0138
RESID(-1)^2	0.186437	0.042426	4.394393	0.0000
GARCH(-1)	0.797752	0.037916	21.03995	0.0000
T-DIST. DOF	5.768924	1.109677	5.198743	0.0000
Generalized error distribution (GED)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.005221	0.001228	4.253179	0.0000
RLOGBP	0.344501	0.030045	11.46607	0.0000
Variance Equation				
C	7.88E-05	2.82E-05	2.790383	0.0053
RESID(-1)^2	0.175998	0.041390	4.252210	0.0000
GARCH(-1)	0.800200	0.039149	20.43963	0.0000
GED PARAMETER	1.321795	0.078263	16.88920	0.0000

In the model under all tested distributions in table 4.8, ARCH and GARCH estimates in the conditional variance equations are significant at 1%, 5% and 10% conventional levels of significance. The previous days' residual variances or GARCH terms, in the variance equations under different conditional distributions have p-values of "zero" leading to rejection of the null hypotheses ($H_{0:}$*GARCH term does not have influence on the RTS Index returns volatility*).

Coefficient values of the conditional residuals under all distributions tested are negative stating that the model is significant.

The assessment of the volatility shocks in the GARCH-based models is performed using the summation of the ARCH and GARCH terms of the models under the 3 different distributions to check the validity of the results. The sums of ARCH and GARCH coefficients under the Normal distribution, Student's t distribution and GED distribution are 0.9721, 0.9842 and 0.9762 respectively; since all of the values are close to one, it indicates that the volatility shocks are persistent. Same results are usually "observed in high frequency financial data." [1]

The estimation output is provided through computing mean and variance equations. The results for the GARCH under the Normal Distribution and the GED Distribution were received after 13 iterations, while it required only 11 iterations to achieve convergence under the Student's t distribution. The GARCH model in this research computed the pre-sample variance in the case of backcasting with a smoothing parameter of 0.7 in all 3 distributions.

In the GARCH model analysis the results of the ARCH coefficients are rather small indicating that conditional volatility does not fluctuate swiftly due to the implications of the oil returns, but the volatility tends to change rapidly because of the high degree of GARCH estimates. The shocks or the periods of increased volatility movements in the Brent oil market accelerate the fluctuations in the RTS returns.

4.6. Discussion

Dependent Variable: RLOGIV		
Method: ML - ARCH (Marquardt) - Normal distribution		
Sample (adjusted): 2000M04 2012M05		
Included observations: 146 after adjustments		

[1] *EViews 7 User's Guide II* (Quantitative Micro Software, 2012), 204.

Convergence achieved after 11 iterations				
Presample variance: backcast (parameter = 0.7)				
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) + C(6)*INFL + +C(7)*INDPROD + C(8)*M2 + C(9)*EXC				
Mean Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.011327	0.006887	1.644746	0.1000
RLOGBP	0.457686	0.083368	5.489964	0.0000
Variance Equation				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.042201	0.006024	7.005433	0.0000
RESID(-1)^2	0.119517	0.076696	1.558319	0.1192
GARCH(-1)	0.620030	0.162374	3.818531	0.0001
INFL	4.39E-06	1.65E-05	0.266218	0.7901
INDPROD	-0.000220	1.85E-05	-11.90974	0.0000
M2	3.03E-07	1.97E-07	1.538052	0.1240
EXC	-0.000511	0.000150	-3.417756	0.0006

In this research, I tested the volatility transmission effect from the logarithmic returns of the Brent oil to the logarithmic returns of the RTS Index representing the Russian stock market. And the results show that the volatility spillover effect does take place and the volatility on the oil market plays a significant role in price determination of the leading Russian energy companies.

Volatility of the Russian stock market depends not only on the behavior of the world oil prices, but also on country’s economic well-being, macroeconomic indicators and other external factors. I have tried to determine extra explanatory variables for the volatility interconnection under the GARCH model. Endogenous variables such as inflation, industrial production, USD/RUB exchange rate and M2 are presented on the monthly basis and are taken into the model to determine the possible existence of volatility transmission onto the RTS Index monthly logarithmic returns, keeping the Brent oil monthly logarithmic returns as an independent variable as in the main model.

In the mean equation, I work on the residual to estimate its variance and determine whether the effect of the Brent oil returns still weigh onto the future volatility of the RTS Index returns. The p-value of the RLOGBP is equal to 0 and with a 5% significance level; it means that the residual variance of the Brent oil logarithmic returns is significant to the volatility spillover to the RTS Index returns.

ARCH-term in the system (RESID(-1)^2) is not sufficient to explain the volatility of the RTS Index returns, since its p-value is 0.1192 (11.92%) and is higher than the 5% level of significance. The GARCH-term, which designates past variances of the RTS Index, with a p-value of 0.0001 does affect the future variance movements and is significant under the 5% significance level.

Variance regressors show different influence dynamics on the volatility of the RTS Index monthly logarithmic returns. Data for inflation is considered insignificant based on the results of the p-value of 0.7901, so as the endogenous variable M2 with the p-value of 0.1240, which does not affect the variance of the dependent parameter under the 5% level of significance. On the contrary, indicators such as USD/RUB exchange rate and industrial production show significant results with p-values 0.0006 and 0.0000 respectively, providing evidence that the parameters help to explain the future volatility of the RTS Index monthly logarithmic returns.

Limitations on this research can affect on the data frequency and choice of selected endogenous variables to test the explanatory power of the independent variable’s volatility (Brent oil logarithmic returns) onto the fluctuations of the Russian stock market, presented by the RTS Index logarithmic returns. Monthly data for the second GARCH modeling was chosen because of the availability of the frequency data for the macroeconomic indicators: inflation, M2 and industrial production. I have chosen those variables on the basis of following criteria:

1. significance of economic data for the research topic;
2. accessibility of a range of data set with low frequency;
3. consistency of the data sets during the analyzing period;
4. reliability of the data sources.

The data for the exchange rate was transformed into monthly values to provide a dataset consistent with other variables in the system and it was transformed through averaging daily exchange rates in a single month. The reason of the exchange rate inclusion in the model testing lies in its influence on the RTS Index value determination. Most of the stocks included in the RTS Index calculation are quoted in rubles and, then, through exchange rate transformed via exchange rate to present the Index's value in U.S. Dollars.

The data period in the monthly sample only covers the period since the beginning of 2000, and not since 1995, when the RTS Index started to be quoted, because most of the consistent macroeconomic data in Russia including M2 and industrial production started to be accessible from the year 2000.

I have tried to use the effect of the endogenous variables in absolute terms on the volatility of the logarithmic returns of the RTS Index, and it might have brought inconsistency in the results, but the variance regressors' values in the model obtain more explanatory power rather than their returns.

Limitations of this study may include the use of a simple GARCH (1, 1) model to explain the volatility spillover effects of the oil and stock markets in Russia. More sophisticated GARCH-based specifications are found to be useful in a good use of explaining this type of volatility relationship. Ling and McAleer (2003) developed the VAR(1)–GARCH(1, 1) model to examine volatility transmissions through dynamic conditional correlations; the GARCH-BEKK model proposed by Engle and Kroner (1995) can successfully estimate bivariate linkages between financial markets, or exponential GARCH (EGARCH) can model the volatility of a variable and provide good results especially on the markets that have experienced price shocks.

Further research under the topic of the volatility interdependencies between markets can proceed to compare the volatility transmission in Russia and Eastern European countries, or countries BRICS. In order to strengthen the evidence on the link between oil and stock markets, the research may run a volatility model on other oil-exporting countries and compare the estimated results.

The Russian financial market is still under the process of development, especially the Russian bond market. The identification of the variables that have explanatory factors over the interest volatility of the Russian bonds would significantly help its further development.

The current research needs to look further at the applications of the results and the ways to model the volatility data in order to settle prices on different equities on the stock and derivative markets.

5. Conclusion

In this research I examine the volatility response of the Russian stock market to world oil price changes. An application of the GARCH-based model is suggested to check the strength of the volatility dependencies and identify the effect of past innovations on the future volatility values. The reason to run a volatility analysis is significant because of the increasing dependency of the Russian economy and financial markets on oil and gas revenues.

The development of the Russian economy, increase in industrial production and acceleration in people's well-being for over a decade from 1998 to 2008 have been largely subsidized by rising prices of the main Russian export commodities. In 2008-2009 during the World economic and financial crisis, Russian economy declined by nearly 8% in terms of GDP and the RTS Index lost 75% of its value. Also, the Central Bank of Russia spent $157Bn. or 27.5% of its international reserves, in 2008-2009 to slow the ruble's devaluation. The crisis showed how much Russia had been depended on the price fluctuations on its major commodities on international markets, making the research on between-markets volatility interrelations more valuable for policy-making, equity price setting, and expansion of hedging opportunities.

The application of the simple GARCH (1, 1) model on between-markets volatility in Russia is described by the stochastic model projecting the RTS Index logarithmic returns volatility in the correspondence with the Brent oil price logarithmic returns on the weekly basis observations.

The analysis of data sets shows that the distributions of both the oil price returns and the RTS Index returns have a positive excess kurtosis (or leptokurtic) in a form of sharp peaks and heavy tails. High levels of kurtosis for the both variables' values are the consequences of high inconsistent volatility of the variances during the time period. At the same time, both data series provide negative skewness results, where distributions are skewed to the left side of the probability density function.

The ADF Test presents no sign of the autoregressive unit root for both variables with p-value consistently lower than 5% level of significance under all 3 options in regard with trend statistics. Combined results provide sufficient evidence that the data for the weekly RTS Index returns are stationary.

This paper provides 4 major findings associated with interrelation between the world oil price returns and the Russian stock market returns:

First, the result of the Johansen sequential Testing procedure using Unrestricted Cointegration Rank Test (trace statistic technique) shows that the null hypothesis (there is no cointegration between variables) should be rejected since p-value is 0.0001. It can be concluded from the Vector Autoregression model that there is possibly a long-run association between oil and stock returns.

Second, the Granger Causality Test suggests that the past values of the Brent oil returns contribute to the prediction of the present value of the RTS Index returns together with the past values of the RTS Index return values. The values of F statistic suggest that the Brent oil logarithmic returns Granger-cause the RTS Index logarithmic returns. At the same time, the model projects no evidence of a reverse causality relationship, meaning the RTS Index returns do not Granger-cause the movements in the Brent logarithmic weekly returns.

Third, the results of the research demonstrate that the oil price fluctuations have a strong impact on the volatility of the Russian stock market returns, and provide empirical evidence that the conditional volatility of the RTS Index is heavily influenced by its past innovations. The GARCH term in the model under 3 different distributions (i.e. Normal distribution, Student's t distribution and GED distribution) shows consistent results of the past variance and its predictive power on the future values of the RTS return volatility.

Forth, the volatility of the Russian Stock market depends not only on the behavior of the world oil prices, but also on some macroeconomic factors. Inflation, industrial production, USD/RUB exchange rate and M2 are the endogenous variables that were tested on the monthly time basis in the GARCH model. Only the USD/RUB exchange rate and the industrial production indicators show significant results with p-values 0.0006 and 0.0000 respectively, providing evidence that the parameters help to explain the future volatility of the RTS Index monthly logarithmic returns. The model with variance regressors shows different influence dynamics on the volatility of the RTS Index logarithmic returns. The ARCH-term in the system with endogenous variables is not significant to explain the volatility of the RTS Index returns, since its p-value is 0.1192 (11.92%), while the indicator of previous returns shows explanatory power in the system without variance regressors.

Russian economic and financial systems are still developing, moving towards further integration processes with the world financial markets. In order to build a strong economy and sustainable financial system, it is crucial to determine the interrelations and volatility dependencies between different financial markets: both domestic and international. Strong results on volatility transmissions help to establish applications of the results in the ways to model the volatility data in order to design proper policies, settle prices on different equities and hedge instruments on stock and derivative markets.

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