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IMPACT OF RUSSIA'S 2014–2015 CRISIS ON THE DYNAMIC LINKAGES BETWEEN THE STOCK MARKETS OF RUSSIA, THE EU AND U.S.

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Abstract

One of the most recent turmoil periods of significant importance is the ongoing Russian financial crisis that started in 2014. Considering the openness of the Russian economy, it might be that this disruptive event could have had an impact on the linkages between Russian and other global stock markets. This paper analyses changes in the dynamic linkages between the U.S., EU and Russia's stock markets in the midst of the Russia's 2014-2015 crisis. This study is particularly concerned with analysing how short-run, long-run and volatility transmission linkages have changed due to the Russian crisis. We performed a structural break analysis to identify a period of tranquillity in the Russian stock market and the date on which the crisis period started. Afterwards, we run cointegration, Granger-causality, impulse response, variance decomposition and GARCH-BEKK tests to compare long-run, short-run, shock spillover and volatility spillover linkages during the stable and the crisis periods.

We found that there are changes in the short-run, long-run and volatility linkages among the stock markets of the U.S., EU and Russia during the crisis period. Consistent with the idea that there is a financial crisis in Russia, return shocks in the Russian stock market are substantially higher during the crisis period than they were during the stable period. Also, during the crisis period stock market of Russia seems to be less sensitive to return shocks from the EU stock market and vice-versa. We consider that the bilateral sanctions between Russian and the EU might have contributed to the segregation of their stock markets. In addition, we discovered that there are greater short-run and long-run diversification benefits during the turmoil period. However, the results of the GARCH-BEKK model suggest that there is a contagion effect from the Russian stock market to the stock markets of the U.S. and the EU. Thus, investors should be aware of shock and volatility spillovers among these countries' equity markets while assessing the risk of their portfolios. In addition, the results are robust even if the stable and the crisis periods are determined using historical, not implied volatility.

Keywords: Russia's 2014-2015 crisis, returns spillover, volatility spillover, GARCH-BEKK

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1 Introduction

Over the last few decades, dynamic linkages between international markets has been a hot topic, not only among academicians, but also among banks, international investors, hedge funds and various other institutions. Particular interest in this topic was seen during the 2008 financial crisis, when a shock in the U.S. market brought down not only the domestic stock market, but also markets overseas and destabilized the Euro Zone which led to the European sovereign debt crisis (Fontaine, 2011). Thus, one should not underestimate the power of the information transmission mechanism among various markets.

How the 2014-15 Russian crisis have impacted the dynamic linkages across financial stock markets is an important research question for many reasons. First, to our knowledge, this paper is a pioneer in this field. Taking into account that previous research papers suggest that there is little evidence of contagion from the Russian equity market during recent crises (Claessens & Forbes, 2004) and that the Russian stock market is highly integrated, a substantial increase in the dependence between it and other markets is unlikely (Korhonen & Peresetsky, 2013), it is of interest for us to test the validity of these conclusions in the context of the current Russian crisis. Second, taking into account that the EU and the U.S. are two superpowers which imposed most sanctions on Russia due to its military intervention in Ukraine in 2014, it is interesting for us to analyze the feedback effect coming from the plummeting stock market of Russia to the stock markets of the EU and the U.S. Third, this study will reveal information regarding equity market efficiency of the previously mentioned countries, since in an efficient market it is not possible to forecast returns by conditioning them on the lagged returns of other related markets. Fourth, knowledge of volatility interdependence may improve current estimates of conditional volatility, which is useful for the following financial applications: options pricing, value-at-risk (VaR) estimation, portfolio optimization, hedging, strategic asset allocation and market selection. Last but not least, in the case that evidence of contagion is found, this study might be useful for government officials, investors and policymakers to strengthen individual economies and international financial systems in order to reduce the risk of contagion in the future by implementing better financial policies, by using improved investor strategies or by creating stronger global frameworks.

Initially, we would like to define the main concepts of our study, namely interdependence, integration and contagion. *Interdependence* can be considered as a stable state of dependence between capital markets (Trenca & Dezsi, 2013). In our paper we examine short-term (return) and long-term (price) interdependence among stock markets. The next two terms, namely integration and contagion, are related to shock and volatility spillover among equity markets. *Integration* can be defined as a high degree of dependence among equity markets that is not affected by an external shock. If two markets share a high degree of dependence during the periods of stability, and the co-movement between them after an external shock does not increase significantly, then this phenomenon is called integration rather than contagion. Forbes and Rigobon (2002) asserted that in case of a true *contagion* to take place, there should be no prior dependence between stock markets before the occurrence of a financial distress. Taking into account the considerable development of technology and the increased flow of capital between countries, which catalyzed the globalization process, it is almost impossible for stock markets to be independent. Therefore, it is more appropriate to define contagion as an increase in shock and volatility dependence between equity markets during a financial distress period compared to their levels of dependence during a predefined stable period.

The rest of the paper is structured as follows. Section 2 outlines the literature on interdependence and contagion. Section 3 describes the methods used to answer the research questions. Section 4 specifies data gathering and section 5 provides and discusses the results. Further, section 6 examines the robustness of the results and section 7 draws conclusions from the results acquired in the previous section. Next, section 8 provides implication of the results, and we conclude the paper with section 9 that discusses the limitations of the study and suggest further research possibilities regarding the Russia's 2014-2015 crisis and its impact on the dynamic linkages between stock markets.

2 Literature Review

Numerous studies have researched the dynamic linkages between stock markets.Tuluca and Zwick (2001) found that during the 1987 stock market crash short-term co-movements between the U.S. and the UK increased substantially. The same conclusion of increased short-run linkages during a crisis period is found by Jochum, Kirchgassner & Platek (1999) who studied Polish, Hungarian, Czech, Russian and the U.S. stock markets during the Asian crisis in 1997 and during the subsequent Russian crisis in 1998. In addition, Gabriel and Manso (2014) investigated changes in the short-term linkages during the Dot-Com crisis and during the Global financial crisis and found that during both crises short-term linkages between twelve European and non-European equity markets increased.

Speaking about the long run linkages, Tuluca and Zwick (2001) found that the stock market crash in 1987 did not affect the long-term linkages between the U.S. and the UK. Also, Voronkova and Lucey (2005) did not find any long-run co-movement between Russia, UK, U.S., Hungary and Poland stock markets before, during and after the Asian and the subsequent Russian crisis from 1998. Whereas, Inder (2014) suggested that Indian stock market has become more cointegrated with stock markets of other Asian countries after the subprime crisis. Similarly, Lee and Jeong (2014) advocated that the level of cointegration between the European and global stock markets had temporarily increased during the subprime crisis.

One can see that short-run and long-run linkages between various equity markets might change over time and they are particularly susceptible to the turmoil periods.

It is of interest for us to analyze short-term and long-term dynamic linkages between the EU, U.S. and Russian stock markets prior to the recent 2014-2015 Russian crisis and whether this crisis has had any effect on those linkages. Thus we draw the following two research questions:

1. Have the long-run linkages between the stock markets of the U.S., Russia and the EU changed due to the Russia’s 2014-2015 financial crisis?

2. Has the short-run return transmission between the stock markets of the U.S., Russia and the EU changed due to the Russia’s 2014-15 financial crisis?

Volatility and shock transmission is high during periods of crises, because investors attempt to discover price changes in one market using observed fluctuations in other equity markets (Maghyereh and Awartani, 2012). Hamao, Masulis & Ng (1990) in their research concluded that volatility spilled over from New York to London stock exchange during the

1987 U.S. stock market crash. Kharchenko and Tzvetkov (2013) also observed this phenomenon during the 2008 financial crisis when volatility and shocks spilled from German and French stock markets to the Russian equity market and from Russian to the U.S. equity markets. A different view on the direction of the volatility and shock spillovers from Russia to the U.S. is presented by Khan (2010) who found a bidirectional link between both countries' equity markets, whereas Dimitriou, Kenourgisos & Simos (2013) suggested that volatility was spilled from the U.S. to Russian equities, thus suggesting a third view about the volatility linkage between the U.S. and Russia during the sub-prime crisis in 2008. Despite the discussion on the direction of volatility and shock spillovers, Claessens and Forbes (2004) who analyzed financial crises in 1990s and the Argentinean and Turkish crises between 2001 and 2002 concludes that the contagion effect has become rare during financial crises as countries have employed better fiscal and monetary policies. The authors also state that there is little evidence of contagion effect from Argentinian and Turkish crisis. Furthermore, Korhonen and Peresetsky (2013) suggest that the Russian stock market is already highly integrated with the EU and the U.S. equity markets, thus an increase in dependence through volatility and shock spillovers between Russia and other equity markets is unlikely.

Taking all of the above findings into account, we draw our third RQ:

3. Have the volatility transmission linkages between the stock markets of the U.S., Russia and the EU changed due to the Russia's 2014-15 financial crisis? What is the direction of the shock and volatility spillovers?

In order to answer our research questions, we will analyze changes in price, return and volatility linkages among Russia, the U.S. and the EU. The latter two regions were chosen by the authors due to several reasons. The major reason is that they are the ones that have imposed most of the sanctions on Russia, because they considered its intervention in Ukraine unlawful (Klapper, 2014; Norman & White, 2014). Another reason why we chose to analyze the changes in volatility, price and return linkages with the EU and with the U.S. in the context of Russian crisis is that both of them are major superpowers in the world (Guttman, 2001; Herring, 2008), thus it would be interesting for us to examine the effect of plummeting Russian stock market on such big world "players". Moreover, the EU is not only the major trading partner of Russia, but it is also its most important investor. It is estimated that in 2013 around of 75% of FDI stocks in Russia came from the EU member states (European Commission, 2014). On the other hand, although the U.S. trade balance with Russia is much less, the Russian market still remains attractive for the U.S. companies, such as *ExxonMobil*, *Boeing*, *Chevreon*, *Coca-Cola* etc, which have invested more than $30 billion in the period from 1992-2011 (Borisov & Frye, 2011).

In sum, the purpose of this paper is to rigorously investigate the impact of the Russian financial crisis, which commenced in 2014, on the equity markets of two major world players, namely the United States and the European Union, by analyzing changes in the dynamic linkages among these stock markets. Numerous studies have researched the dynamic linkages between stock markets.Tuluca and Zwick (2001) found that during the 1987 stock market crash short-term co-movements between the U.S. and the UK increased substantially. The same conclusion of increased short-run linkages during a crisis period is found by Jochum, Kirchgassner & Platek (1999) who studied Polish, Hungarian, Czech, Russian and the U.S. stock markets during the Asian crisis in 1997 and during the subsequent Russian crisis in 1998. In addition, Gabriel and Manso (2014) investigated changes in the short-term linkages during the Dot-Com crisis and during the Global financial crisis and found that during both crises short-term linkages between twelve European and non-European equity markets increased.

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3 Methodology

Initially, we test for structural breaks in order to find a relatively stable period in the Russian stock market. Also, by performing the same test we seek to find the date when the crisis started in Russia. Cointegration tests measure the linkage between stock markets in the long run, while the other three tests (Granger-causality, variance decomposition and impulse response) are used to measure the short-run linkages among equity markets. If cointegration is found, it means that even if variables are non-stationary, they do not diverge in the long run. On the other hand, if variables are not cointegrated, then there is no long-run linkage between them. If cointegration exists, then Granger-causality, variance decomposition and impulse response tests should be built on error-correction models. If no cointegration is found, then the tests are run on the first difference of variables by employing a vector autoregressive (VAR) model. Granger-causality is used to analyze the direction of the causality between time series, while variance decomposition and impulse response tests examine duration, speed of the interactions and the contribution of returns innovations in one equity market to the variance of returns in another stock market. Volatility and shock spillovers are computed using a multivariate GARCH-BEKK model.

3.1 Identification of structural breaks

In order to find the range of the stable period and the first day of the Russian crisis from 2014-15, we performed the Bai and Perron (1998, 2003) structural break date identification methodology. Similar approach was used by Heinonen (2013) to determine the starting date of the global financial crisis. The Bai and Perron regression equation can be defined as follows:

$$\boldsymbol{\sigma_t = \theta_j + \varepsilon_t}, \text{ t=} \boldsymbol{T_{j-1} + 1, \dots, T_j} \text{ and } \boldsymbol{j = 1, \dots, m+1} \qquad (1)$$

where σ_t is the *RTS Volatility Index* at time t, θ_j is the mean of the volatility in the j'th regime, where $j = 0, \dots, m$; ε_t is the error term. The parameter m is the number of breaks.

Before running the Bai-Perron structural break test it is important to check whether $\sigma_t$is stationary (Heinonen, 2013). If the volatility series have unit root then the results provided by this test are unreliable.

3.2.1 Vector autoregressive (VAR) model

Generally, if $\overrightarrow{Y_t} = (y_{1t}, y_{2t} \dots y_{nt})'$ denotes an $(nx1)$ vector of time series variables, the $VAR(p)$ model would look as follows:

$$\boldsymbol{Y_t = C + \sum_{i=1}^{p} A_i Y_{t-1} + \Psi D_t + \varepsilon_t, \quad t = 1, \dots, T,} \tag{2}$$

Where A_i is an (nxn) coefficient matrix and ε_t is an $(nx1)$ zero mean white noise vector process, C is a vector of constants and D_t is a vector of deterministic variables, such as linear trends, seasonal dummies.

In a VAR model all variables should be stationary, but financial stock/index price series are usually non-stationary; therefore, the VAR model shall be transformed into Vector Error Correction Model (VECM), which drops out the requirement regarding the stationarity of the data.

To choose the optimal lag length we will rely on models that minimize information criteria. Particularly we will focus more on SBIC specification because it is more parsimonious, while the AIC will choose on average a model with too many lags.

3.2.2 Vector Error Correction Model (VECM)

Taking into account the $VAR(p)$ equation which we wrote in the previous sub-section (see equation 2), our VECM model looks as follows:

$$\Delta \mathbf{Y_t} = \mathbf{C} + \Pi \mathbf{Y_{t-1}} + \sum_{\mathbf{i=1}}^{\mathbf{n-1}} \Phi_{\mathbf{i}} \Delta \mathbf{Y_{t-i}} + \boldsymbol{\Psi D_t} + \boldsymbol{\varepsilon_t} \tag{3}$$

where $\Pi = (\sum_{i=1}^{n} A_i - I)$ and $\Phi_{\mathrm{i}} = -\left(\sum_{j=i+1}^{n} A_j\right)$.

3.3 Cointegration test- Johansen approach

In order to investigate *long-run relationship* between variables in multivariate models, we will use the Johansen cointegration test (Johansen, 1991). The core of the Johansen method relies on testing for cointegration by looking at the rank of the Π matrix via its eigenvalues (characteristic roots).

3.3.1 Testing for the rank of Π matrix

The Johansen test analyzes whether the restrictions imposed on the rank of Π matrix can be rejected (Huyghebaert & Wang, 2010). The rank of the matrix is equal to the number of eigenvalues (λ_i) which are different from 0. If the variables are not cointegrated, the rank of Π will be almost zero, i.e $\lambda_i \approx 0$.

To test for cointegration rank two likelihood tests can be used: trace statistics and maximum eigenvalue statistics. In this work we do not prefer one statistic over the other, but we will consider the results of both of them while drawing our conclusions.

3.3.2 Selection of the deterministic components in the Johansen test

Assuming that k=2 and $D_t = t$ we can rewrite equation 3 as:

$$\Delta\mathbf{Y_t} = \mathbf{C} + \boldsymbol{a\beta}'\mathbf{Y_{t-1}} + \Phi_{\mathbf{1}}\Delta\mathbf{Y_{t-1}} + \mathbf{\Psi t} + \boldsymbol{\varepsilon}_{\mathbf{t}} \tag{4}$$

where t is a time trend variable. Following (Ahking, 2002), we can decompose C and $\mathbf{\Psi}$ into

$$\mathbf{\Psi} = \boldsymbol{a}\mathbf{\Psi_1} + \boldsymbol{a_0}\mathbf{\Psi_2} \tag{5}$$

$$\boldsymbol{C} = \boldsymbol{a}\boldsymbol{C_1} + \boldsymbol{a_0}\boldsymbol{C_2} \tag{6}$$

where $\mathbf{\Psi_1}$is a r-dimensional vector of linear trend coefficients in the cointegrating relationship; $\mathbf{\Psi_2}$ is an $(n-r)$ dimensional vector of quadratic trend coefficients in the data; $\boldsymbol{C_1}$ is a r-dimensional vector of intercepts in the cointegrating relationship; $\boldsymbol{C_2}$ is an $(n-r)$-dimensional vector of linear trend slope coefficients in the data. Substituting Equations (6) and (5) into Equation (4), we get

$$\Delta\mathbf{Y_t} = \boldsymbol{a}\begin{pmatrix}\boldsymbol{\beta} \\ \boldsymbol{C_1} \\ \mathbf{\Psi_1}\end{pmatrix}' \mathbf{Y_{t-1}} + \Phi_{\mathbf{1}}\Delta\mathbf{Y_{t-1}} + \boldsymbol{a_0}\boldsymbol{C_2} + \boldsymbol{a_0}\mathbf{\Psi_2}\mathbf{t} + \boldsymbol{\varepsilon}_{\mathbf{t}} \tag{7}$$

Depending on the restriction on $\mathbf{\Psi_1}, \mathbf{\Psi_2}, \boldsymbol{C_1}, \boldsymbol{C_2}$, the deterministic components can designed in five different ways which are summarized in Table 1 starting from the most restrictive (Case 1) to the least restrictive (Case 5) (Ahking, 2002). Since cases 1 and 5 are quite atypical, in this research only models 2-4 will be considered.

Table 1 Restrictions on deterministic components

	Restrictions
Case 1	$\mathbf{\Psi_1} = \mathbf{\Psi_2} = \boldsymbol{C_1} = \boldsymbol{C_2} = \mathbf{0}$
Case 2	$\mathbf{\Psi_1} = \mathbf{\Psi_2} = \boldsymbol{C_2} = \mathbf{0}; \boldsymbol{C_1} \neq \mathbf{0}$
Case 3	$\mathbf{\Psi_1} = \mathbf{\Psi_2} = \mathbf{0}; \boldsymbol{C_2} \neq \mathbf{0}; \boldsymbol{C_1} \neq \mathbf{0}$
Case 4	$\mathbf{\Psi_2}=0; \mathbf{\Psi_1} \neq \mathbf{0}; \boldsymbol{C_2} \neq \mathbf{0}; \boldsymbol{C_1} \neq \mathbf{0}$
Case 5	$\mathbf{\Psi_2} \neq 0; \mathbf{\Psi_1} \neq \mathbf{0}; \boldsymbol{C_2} \neq \mathbf{0}; \boldsymbol{C_1} \neq \mathbf{0}$

3.4 Granger causality test

Granger causality is an econometrics tool based of F-test methodology to determine whether one series is helpful at predicting the future values of other series, conditioning on its past values.

When we conduct a linear Granger causality test, we should account for two cases, deending on whether variables of interest are cointegrated or not.

i) In the case all N variables are non-cointegrated, the following $VAR(p)$ model in the matrix form is estimated:

$$\begin{pmatrix} \Delta \boldsymbol{Y_{1,t}} \\ \Delta \boldsymbol{Y_{2,t}} \\ \vdots \\ \Delta \boldsymbol{Y_{n,t}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{A_{10}} \\ \boldsymbol{A_{20}} \\ \vdots \\ \boldsymbol{A_{n0}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{A_{11}(L)} & \boldsymbol{A_{12}(L)} & \cdots & \boldsymbol{A_{1n}(L)} \\ \boldsymbol{A_{21}(L)} & \boldsymbol{A_{22}(L)} & & \boldsymbol{A_{2n}(L)} \\ & \vdots & \ddots & \vdots \\ \boldsymbol{A_{n1}(L)} & \boldsymbol{A_{n2}(L)} & \cdots & \boldsymbol{A_{nn}(L)} \end{pmatrix} \begin{pmatrix} \Delta \boldsymbol{Y_{1,t-1}} \\ \Delta \boldsymbol{Y_{2,t-1}} \\ \vdots \\ \Delta \boldsymbol{Y_{n,t-1}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon_{1,t}} \\ \boldsymbol{\varepsilon_{2,t}} \\ \vdots \\ \boldsymbol{\varepsilon_{n,t}} \end{pmatrix} \tag{8}$$

Where $(Y_{1,t}, \dots, Y_{n,t})$ is a vector of n stationary index price time series at time t, L is backward operator, so that Lx_t=x_{t-1}, A_{i0} are intercept parameters, $A_{ij}(L)$ are polynomials in the lagged operator L, such that $A_{ij}(L) = a_{ij}(0)L^0 + a_{ij}(1)L^1 + \cdots + a_{ij}(p-1)L^{p-1}$. Since our lagged terms' coefficient matrix is of size (nxn), we have to test $n(n-1)$ null hypotheses of (non-) Granger causality.

ii) If variables are cointegrated, Error Correction Mechanism (ECM) must be added to equation 8, therefore, the following model will be tested:

$$\begin{pmatrix} \Delta \boldsymbol{Y_{1,t}} \\ \Delta \boldsymbol{Y_{2,t}} \\ \vdots \\ \Delta \boldsymbol{Y_{n,t}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{A_{10}} \\ \boldsymbol{A_{20}} \\ \vdots \\ \boldsymbol{A_{n0}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{A_{11}(L)} & \boldsymbol{A_{12}(L)} & \cdots & \boldsymbol{A_{1n}(L)} \\ \boldsymbol{A_{21}(L)} & \boldsymbol{A_{22}(L)} & & \boldsymbol{A_{2n}(L)} \\ & \vdots & \ddots & \vdots \\ \boldsymbol{A_{n1}(L)} & \boldsymbol{A_{n2}(L)} & \cdots & \boldsymbol{A_{nn}(L)} \end{pmatrix} \begin{pmatrix} \Delta \boldsymbol{Y_{1,t-1}} \\ \Delta \boldsymbol{Y_{2,t-1}} \\ \vdots \\ \Delta \boldsymbol{Y_{n,t-1}} \end{pmatrix} + \begin{pmatrix} \aleph_0 \\ \aleph_1 \\ \vdots \\ \aleph_n \end{pmatrix} (\boldsymbol{\varepsilon_{t-1}}) + \begin{pmatrix} \boldsymbol{u_{1,t}} \\ \boldsymbol{u_{2,t}} \\ \vdots \\ \boldsymbol{u_{n,t}} \end{pmatrix} \tag{9}$$

In this case we only introduce lagged error terms from the previously mentioned $VAR(p)$ model.

3.5 Generalized impulse response function

VAR's impulse response function analyzes how the dependent variable reacts to shocks from each independent variable. Lütkepohl and Reimers (1992) suggested that traditional impulse response analysis requires the orthonagolization of shocks and the results of the analysis vary with the ordering of the variables in VAR: the higher the correlations between residuals, the more important variable ordering is. In order to overcome this issue Pesaran and Shin (1998) developed the generalized impulse response function which is adjusted for the influence of different ordering on impulse response functions.

Using a tri-variate model, we can denote the matrix of responses to a standardized shock taking place h periods in advance as

$$\boldsymbol{B_h} = \frac{\partial \boldsymbol{y_{t+h}}}{\partial \boldsymbol{\varepsilon_t}'} = \begin{bmatrix} \frac{\partial \boldsymbol{y_{1,t+h}}}{\partial \boldsymbol{\varepsilon_{1,t}}} & \frac{\partial \boldsymbol{y_{1,t+h}}}{\partial \boldsymbol{\varepsilon_{2,t}}} & \frac{\partial \boldsymbol{y_{1,t+h}}}{\partial \boldsymbol{\varepsilon_{3,t}}} \\ \frac{\partial \boldsymbol{y_{2,t+h}}}{\partial \boldsymbol{\varepsilon_{1,t}}} & \frac{\partial \boldsymbol{y_{2,t+h}}}{\partial \boldsymbol{\varepsilon_{2,t}}} & \frac{\partial \boldsymbol{y_{2,t+h}}}{\partial \boldsymbol{\varepsilon_{3,t}}} \\ \frac{\partial \boldsymbol{y_{3,t+h}}}{\partial \boldsymbol{\varepsilon_{1,t}}} & \frac{\partial \boldsymbol{y_{3,t+h}}}{\partial \boldsymbol{\varepsilon_{2,t}}} & \frac{\partial \boldsymbol{y_{3,t+h}}}{\partial \boldsymbol{\varepsilon_{3,t}}} \end{bmatrix} \tag{10}$$

In the above matrix the row 1, column 1of B_h identifies the consequence of one standard deviation increase in the 1st variable at time t, holding all other innovations constant, on the variable $\boldsymbol{y_1}$ h periods ahead.

In this thesis, generalized impulse response functions are used as described by Pesaran and Shin (1998). They are calculated according to the formula:

$$\boldsymbol{\psi_{i,j}^{g}(h)} = \frac{\boldsymbol{B_h \Sigma e_j}}{\sqrt{\boldsymbol{\sigma_{jj}}}} \tag{11}$$

where $\psi_{i,j}^{g}(h)$ refers to the generalized scaled impulse response of endogenous variables at time $t + h$ to an exogenous shock of the error term in the equation j from the VAR model (see equation 2) in the period t, σ_{jj} is the variance of the error term in the equation j, e_j is a $kx1$ selection vector with zero in all but the $j'th$ entry, and Σ is nxn variance-covariance matrix of the error term.

3.6 Variance decomposition

If VAR models have many equations or lags, it becomes more complex to observe the effects of external shocks on its dependent variables. In order to show the interaction between equations we will perform variance decomposition analysis.

Variance decomposition traces out the portion of movements in the depended variables that are due to their own shocks versus shocks of other variables (Brooks, 2002).

The general formula to the forecast error variance k steps ahead can be written as:

$$\boldsymbol{y_{t+k} - \hat{y}_{t+k} = B_0 \varepsilon_{t+k} + B_1 \varepsilon_{t+k-1} + \cdots + B_{k-1} \varepsilon_{t+1}} \tag{12}$$

while

$$\boldsymbol{var_t(y_{t+k}) = \sum_{\tau} \vartheta_{k,\tau}} \tag{13}$$

is the total variance of forecast error at the time $t + k$. It is interesting to compute the decomposition of the actual variance of the series. The contribution of the $\tau'th$ shock to the variance of y_t is given by

$$\boldsymbol{\vartheta_{\tau} = \sum_{j=0}^{\infty} B_j I_{\tau} B_j'} \tag{14}$$

and the general formula for k-step ahead forecast error variance is given by

$$\boldsymbol{var_t(y_{t+k}) = \sum_{\tau} \vartheta_{\tau}} \tag{15}$$

3.7 Multivariate GARCH

In order to model the interactions between the volatility of two or more financial time series, a multivariate GARCH model must be used instead of a univariate one. In multivariate GARCH models, considering a vector of return series R_t of the size $(Nx1)$, we can write:

$$\mathbf{R_t} = \boldsymbol{\alpha_0} + \mathbf{\Gamma R_{t-1}} + \boldsymbol{\varepsilon_t} \tag{16}$$

where R_{t-1} is an $(Nx1)$ vector of lagged returns, Γ is an (NxN) matrix associated with these lagged returns; $\alpha_0$is an $(Nx1)$ vector of intercepts, ε_t is the innovation matrix $(Nx1)$ that stores the innovation term for each market. Further, the innovation matrix can be written as

$$\boldsymbol{\varepsilon_t} = \mathbf{H_t}^{1/2}(\boldsymbol{\theta})\mathbf{Z_t} \tag{17}$$

where $\mathbf{H_t}^{1/2}(\boldsymbol{\theta})$ is a positive definite matrix (NxN) and $\mathbf{Z_t}$ is assumed to be an $(Nx1)$ $i.i.d$ vector, with E(Z_t)=0 and Var(Z_t)=I_N. $\boldsymbol{H_t}$ is the variance-covariance matrix of $\mathbf{R_t}$. In case of a trivariate model the variance-covariance matrix of returns would look as follows:

$$\boldsymbol{H_t} = \begin{pmatrix} \boldsymbol{h_{11,t}} & \boldsymbol{h_{12,t}} & \boldsymbol{h_{13,t}} \\ \boldsymbol{h_{21,t}} & \boldsymbol{h_{22,t}} & \boldsymbol{h_{23,t}} \\ \boldsymbol{h_{31,t}} & \boldsymbol{h_{32,t}} & \boldsymbol{h_{33,t}} \end{pmatrix} \tag{18}$$

where $h_{ij,t}$ is the conditional covariance between country i and country j at time t.

In order to examine volatility spillovers we will employ the Baba, Engle, Kraft, and Kroner (BEKK) version of the multivariate GARCH model, whereby the conditional variance-covariance matrix is a function of the squared own and cross-product of innovation terms, ε_t, and lagged conditional variance-covariance matrix, H_t (Engle & Kroner, 1995). The BEKK parameterization of GARCH can be written as follows:

$$\boldsymbol{H_t} = \boldsymbol{B'B} + \boldsymbol{C'\varepsilon'_{t-1}\varepsilon_{t-1}C} + \boldsymbol{G'H_{t-1}G} \tag{19}$$

where B is upper triangular (NxN) matrix of constants, the element c_{ij} of the symmetric (NxN) matrix C denotes the degree of innovation spillover from market i to market j and the element g_{ij} of the symmetric (NxN) matrix G shows the persistence in conditional volatility from market i to market j. Due to high number of estimated coefficients, in this case 27, we will use a $GARCH(1,1)$ $BEKK$ specification since it has been shown to be a parsimonious representation of conditional variance that can fit many financial time series (Bollerslev et al., 1988).

4 Data

To perform our research, we selected the *RTS*, *S&P 500* and *STOXX Europe 50* indices as proxies for market portfolios of Russia, the EU and U.S.

Taking into account that two of our stock indices (*S&P 500* and *RTS*) are denominated in U.S. dollars and due to consistency and comparability, we converted the *STOXX Europe 50* index into U.S. dollars. Transforming the prices of all indices into a common currency is a usual practice for papers analysing dynamic linkages among stock markets (Valadkhani and Chancharat, 2008; Moroza, 2008; Khan, 2011; Tripti, 2015). The daily historical closing prices of *STOXX Europe 50*, *S&P 500* and *RTS* equity indices, the USD/EUR exchange rate and the *RTS Volatility* index were gathered from the *Thomson Reuters Datastream*.

The following formula was used to obtain the returns of an index:

$$R_{i,t} = ln(P_{i,t}) - \ln(P_{i,t-1})$$

(20)

where:

$R_{i,t}$ shows the return of the index i at time t,

$P_{i,t}$ shows the price of the index i at time t,

$P_{i,t-1}$ shows the price of the index i at time $t-1$.

5 Results

5.1 Determination of Structural Breaks

We performed the Bai-Perron structural break test to find the beginning of Russia's 2014-2015 financial crisis and the period of tranquillity to which we will compare our results. The *RTS Volatility* Index is used as the main volatility indicator; however, as a robustness check, we performed the same test on the annualized daily volatility, computed from historical returns. As both unit root tests (ADF and KPSS) suggest that the *RTS Volatility* Index series is stationary at a 5% significance level (see Appendix A), we can proceed further with the Bai-Peron analysis. According to our test results, the volatility series exhibits five breaks (see Appendix B, C); however, we are interested only in the latest two break dates. The period between 2nd of October 2012 and 3rd of March 2014 exhibit the lowest average volatility, thus we consider it as our stable period. The crisis period, on the other hand, is considered to range between the 3rd of Mach 2014 till 3rd of March 2015. The latest break in volatility occurred one trading day before the Russian Foreign Ministry officially admitted that Russian forces had seized Crimea (Ensor & Merat, 2014; Hufbauer, Cimino & Moran, 2014). Overall, this gives us 369 observations before the crisis and 262 observations during the crisis. Furthermore, the robustness check, using historic instead of implied volatility, provided similar results (see Appendix D, E).

5.2 Tests for Cointegration

Overall, the ADF and KPSS indicate that all level (price) series have a unit root and all return series are stationary during both the stable and the crisis periods. This means that all price series are integrated of order one, $I(1)$. Thus, we can perform Johansen's procedure to determine the number of cointegrating linkages among our variables. The number of lags in the VAR model is determined by SBIC information criteria and in both periods the test suggests to use two lags (see Appendix F). Regarding the parameter specification for Johansen's test, we prefer model 4 over model 2 and 3 as all of our stock index price series have intercepts and that most of the series follow a clear trend.

5.3 The Johansen approach

The results of Johansen cointegration test (Appendix G) suggest that Russian, U.S. and European equity markets were more cointegrated before the crisis than they are afterwards.

This is good news for investors because they can gain substantial long-run benefits due to diversification opportunities.

To determine which long-run associations between the U.S., EU and Russian equity markets that have vanished during the crisis period, we will implement Johansen's cointegration test to each combination of two out of three stock markets (see Appendix H).

After performing a similar analysis as in the tri-variate case, we found that each stock index has a long-run association with other stock indices during the stable period. All cointegrated relationships are significant at a 10% significance level. This long-run association between the Russian and the U.S. equity markets during the stable period is consistent with the results of Zhang et al. (2013), Zhong et al. (2014) and Korhonen and Peresetsky (2013).

During the crisis period we found that there is a significant change in the long-run linkages among the three stock markets we analyze. According to the results of the Johansen test there is no bivariate long-run relationship among any of the stock markets we analyze. This indicates that the diversification benefits can be achieved during the crisis period by investing in any of the stock markets that our analysis is concerned with.

5.4 Short-term linkages

In this part, we present the results of statistical tests examining short-term linkages among the equity markets of Russia, the U.S. and EU during the stable and crisis periods. Initially, we perform a Granger causality test during both periods to determine how the returns from one market influence the returns of other stock markets. The results of the Granger-causality test can also be interpreted as the degree of return spillover from one market to another. Next, we perform an impulse response analysis and a variance decomposition test during the stable and the crisis periods to provide more insights about changes in short-term dynamic linkages.

5.4.1 Return spillover effect: pairwise Granger causality tests

The SBIC suggest using a VAR and VECM model with one lag to perform Pairwise Granger causality tests during the stable and the crisis period (see Appendix I).

Appendix J presents the results of Granger causality tests among different stock markets during the stable period (Panel A) and during Russia's 2014–2015 crisis (Panel B). During the stable period, returns of *S&P 500* Granger caused returns of both *RTS* and *STOXX Europe 50*. Similarly, returns of *STOXX Europe 50* have a statistically significant impact on the returns of other markets, namely on *S&P 500* and *RTS* stock markets. On the other hand, *RTS* returns do not have any forecasting power at predicting returns of either *S&P 500* or of *STOXX Europe 50*.

5.4.2 Impulse response analysis

Even though the Granger causality test shows the source of return spillovers among different stock markets, it does not reveal the sign of the relationship and the duration of these spillovers. We perform an impulse response analysis to gain more information about short-term linkages (return spillovers) among equity markets that we analyze.

Appendix K depicts generalized impulse response functions during the stable and crisis periods: five days' response to one unit of positive innovations from each VAR equation is being considered for all three dependent variables (returns of Russian, the EU and U.S. stock markets). Responses of all three stock markets to the shocks from each other are positive during both (stable and crisis) periods. This suggests that, if the returns of one stock market unexpectedly increase, then the returns of other stock markets increase as well in the very near future. Moreover, the change in returns due to a shock in own stock market is stronger than the change in returns due to shocks received from foreign stock markets. This indicates that the analyzed stock markets do not share a high degree of integration. During the crisis period the EU stock market innovations had a relatively lower impact on the Russian equity market returns than the innovations from the U.S., despite the fact that they had a relatively more significant impact during the stable period. Also, our results imply that Russia's own stock market shocks had a significantly larger impact on its stock market returns during the crisis than they had during the stable period. Regarding the U.S. stock market, impulse response analysis suggests that the impact of the EU stock market innovations is larger than the innovations coming from the Russian market, and this pattern did not change during the Russian crisis. As regards the European stock market, the same test suggests that despite the fact that both the U.S. and Russian market innovations had relatively similar impact on the EU stock market returns initially, during the Russian crisis period the shocks from the Russian stock markets became relatively less significant.

5.4.3 Variance decomposition analysis

We perform the orthogonal variance decomposition procedure of the forecast error up to 1 lag from the VAR and VECM models, based on the returns of each stock market. This analysis will tell us how much of the variance of returns (in percent) of all three stock markets can be explained by shocks originating from each of the three stock markets. The factorization of all three variables was performed using the Cholesky decomposition and the order for Cholesky factorization is 1- returns from *S&P 500*, 2- returns from *STOXX Europe 50* and 3- returns from *RTS*. This ordering is supported by our impulse response analysis, which suggests that innovations from the U.S. stock market act as the major factor influencing the returns in all other stock markets. In addition, empirical literature also suggests that the U.S. stock market is one of the stock markets which has the highest influence on other equity markets (Menezes, 2013). The shocks from the EU stock market are considered to have a lower impact than the ones from the U.S. stock market, while having a more significant influence than the ones from Russian equity market because the EU is considered to be the largest trade partner (U.S. Census Bureau, 2015; BBC, 2014a) and one of the largest investors for both countries (OECD Observer, 2015; European Commission, 2014). The results presented in Appendix L are discussed below.

According to our variance decomposition analysis, the variance of the U.S. equity market returns is highly dependent on internal shocks and this pattern was not changed during the crisis period. On the other hand, the volatility of the EU stock market became less susceptible to shocks originating in the U.S. stock market during the Russian crisis. At the same time, the variance of the Russian equity market became less sensitive to the innovations from the EU market during the turmoil period than during the stable period.

5.5 Multivariate GARCH-BEKK model

This paper uses a trivariate GARCH-BEKK model to quantify the effects of the lagged own and cross-innovations and lagged own and cross-volatility on the present own and cross volatility between the stock markets of Russia, the EU and the U.S. The estimated coefficients of the innovation and lagged variance-covariance parameters during the stable and the crisis periods are presented in the Appendix M.

According to our results, during Russia’s 2014-2015 crisis, there are more shock and volatility spillover linkages between the stock markets of countries that we analyze than there were during the stable period. In addition, all the linkages from the crisis period are more statistically significant than they were during the stable period (see Appendix M). In particular, shocks from Russia are unidirectional during the turmoil period and they seem to influence the volatility of all three stock markets and this impact is more statistically significant during the crisis than during the stable period. These results suggest that there were certain events in the Russian stock market, during the crisis that triggered higher volatility in the foreign markets. In addition, our results suggest that in comparison to the stable period, during the crisis period there was a bidirectional shock spillover between stock markets of the U.S. and the EU (see Appendix M, Panel A). The two-way shock spillover indicates a strong connection between the above-stated equity markets. Generally, bidirectional shock spillovers indicate that news about shocks in one stock exchange affects the volatility of another stock exchange and vice-versa. In this case, shocks from the U.S. equity market to the EU stock market and conversely might have started to be more significant determinants of volatility due to the fact that there was a rise in the foreign direct investments from the U.S. to the EU countries in comparison with the previous years, which strengthened the linkage between these two equity markets (Appendix N). In addition, there were some events that could have led to higher awareness in U.S. stock markets, for example Greek legislative elections from January 2015 and their expected negative impact on the Greek debt crisis (Kottasova, 2015) could have increased the awareness among U.S. investors.

Coefficients of lagged volatility linkages between stock markets that we analyze indicate that during the stable period there were own-volatility spillover linkages in the U.S. stock market, which suggests that past U.S. stock market volatility had a significant impact on its future values. On the other hand, the past volatility of the Russian stock market has a statistical significant impact on the volatility of the EU stock market and on the volatility of its own equity market during the crisis period.

The statistical significance of $g(3,2)$ and the insignificance of $g(2,3)$ during the crisis period (see Appendix M) indicate that the volatility spillover is unidirectional from the Russian stock market to the EU stock market. Additionally, we consider that we do not spot this volatility spillover linkage during the stable period due to the fact that the Russian equity market was relatively tranquil at that time (Appendix B). Thus, this channel of transmission of volatility could have been practically inactive

6 Conclusion

One of the most recent turmoil periods of major significance is the Russian financial crisis that started in 2014. It substantially undermined Russia's economic stability and, given the openness of the Russian economy, we hypothesized that this disruptive period could have an impact on the linkages among global stock markets. In this paper, we analyzed the impact of this crisis on the dynamic linkages among the equity markets of Russia, the U.S. and EU. In particular, we studied the changes in long-term linkages, short term-linkages and the volatility transmission mechanism during the crisis.

(1) First, we performed a Bai-Perron structural break test, which suggested that, there was a significant increase in the average volatility in the Russian stock market in the following day after the Russian Foreign Ministry officially stated that Russian forces had seized Crimea. This is our proxy date for the beginning of the Russia's 2014-15 Russian crisis. (2) Moreover, the same test allows us to identify a period of low volatility (a stable period) against which we compare our results from the crisis period. The stable period was found to be the period that immediately preceded the crisis period.

(3) Our results of the trivariate Johansen cointegration test suggest that there is no long-run association between the equity markets of the U.S., EU and Russia after the 2014-2015 Russian crisis started, despite the fact that there was a cointegrating linkage among all these markets prior to the crisis. (4) By performing a bivariate analysis, we found that there is no long-run linkage between any two of the three countries during the crisis. (5) These results suggest that there are long-run diversification benefits and they can be reaped by investing in any of the three stock markets.

To analyze changes in the short-run linkages between the three stock markets we conducted the Granger-causality, Impulse response and Variance decomposition analyses.

(6) Our results from Granger-causality tests suggest that the EU stock market returns do not Granger-cause the returns of the U.S. equity market during the crisis period, despite the fact that there was a Granger causality linkage during the stable period. (7) An implication of this result is that investors can better diversify their portfolios in the short-run by investing in the U.S. stock market. (8) Moreover, we found that during the crisis period Russian stock market returns have a higher statistical power at Granger-causing the returns of the EU and U.S. stock market than during the stable period. However, the existence of these linkages can still be rejected at conventional significance levels.

(9) Our impulse response analysis suggests that return innovations from each market have a positive impact on other markets' future returns. (10) Also, own-return shocks have a larger

impact on stock markets' future returns than the shocks from foreign stock markets, thus suggesting that the degree of integration among stock markets we analyze is not very high. (11) Regarding the Russian stock market returns, we found that during the crisis period shocks from the EU stock market had relatively lower impact on them than shocks originating in the U.S. stock market, in contrast to the stable period when shocks from the EU stock market were more influential. (12) Similarly, the relative influence of the shocks from the Russian stock market on the EU market is lower during the crisis period than during the stable period. (13) These findings might be well-explained by the idea that the bilateral sanctions between Russia and the EU during the Russia's 2014-2015 crisis could have isolated their stock markets. (14) In addition, consistent with the idea that there is a crisis in Russia, we found that Russian stock market return shocks are far larger during the turmoil period than during the stable period. (15) The same analysis suggests that during both the stable and the crisis periods shocks from the EU equity market had a larger impact on the U.S. equity market than the shocks from the Russian equity market.

(16) The variance decomposition analysis suggests that the variance of returns of the U.S. equity market is significantly affected by internal return innovations and this pattern did not change during the Russian crisis. (17) On the other hand, the variance of returns of the EU stock market became less sensitive to shocks originating in the U.S. during the Russian crisis. One potential explanation for this is that it is not only the Russian stock market which became more isolated, but also the EU's stock market that became more segregated. (18) Further, in comparison with the stable period, we found that the variance of the Russian equity market became less responsive to return shocks from the EU equity market during the crisis period. This is in line with the idea that stock markets of the EU and Russia could have become more isolated.

(19) Finally, the results of our GARCH-BEKK analysis suggest that during the Russian crisis shock spillovers intensified and new volatility spillovers appeared. Taking into account that the Russian crisis was transferred to other stock markets through variance channel by means of shock and volatility spillovers, we conclude that a contagion effect took place among the stock markets of the U.S. and EU during the Russia's 2014-2015 crisis. Also, the results are robust even if the stable and the crisis periods are determined using historical, not implied volatility.

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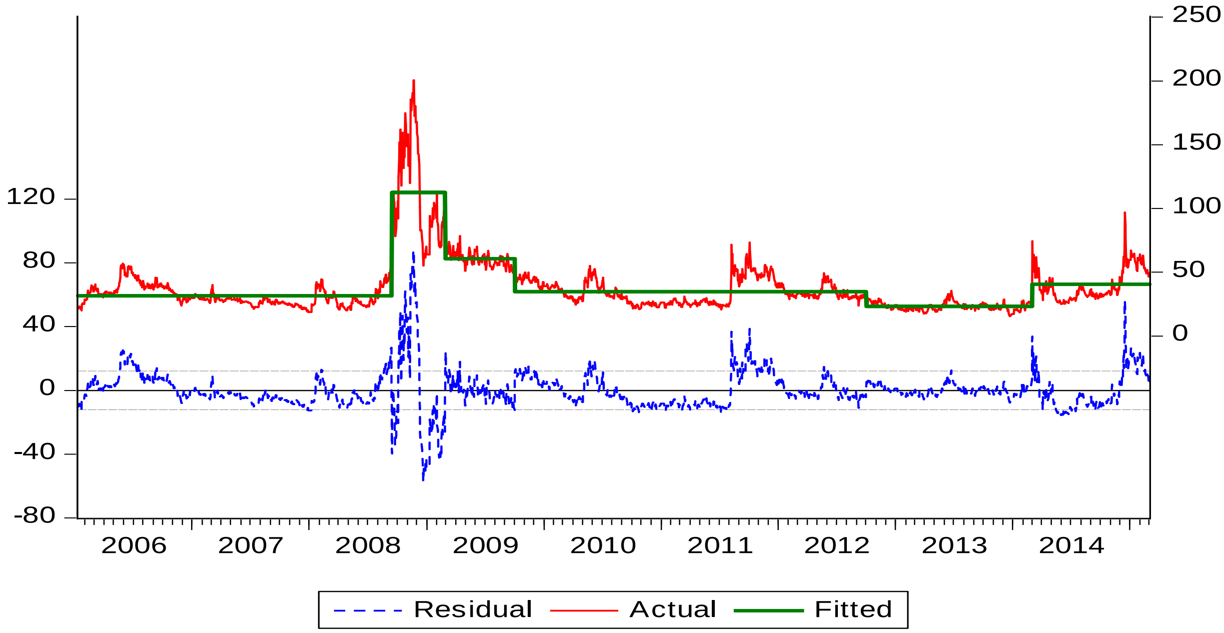
Appendices

Appendix A - Stationarity test for *RTS Volatility* Index, made by the authors using data from *Thomson Reuters Datastream*

ADF		KPSS	
Constant	-3.5158***	Constant	0.4661
Constant & trend	-3.5657**	Constant& trend	0.2574

*,** and *** indicate significance of results at 10% , 5% and 1% significance level, respectively.
Null hypothesis of ADF and PP tests: *RTS* volatility index has a unit root
Null hypothesis of KPSS test: *RTS* volatility index is stationary

Appendix B Structural breaks in the *RTS* implied volatility series, made by the authors using data from *Thomson Reuters Datastream*

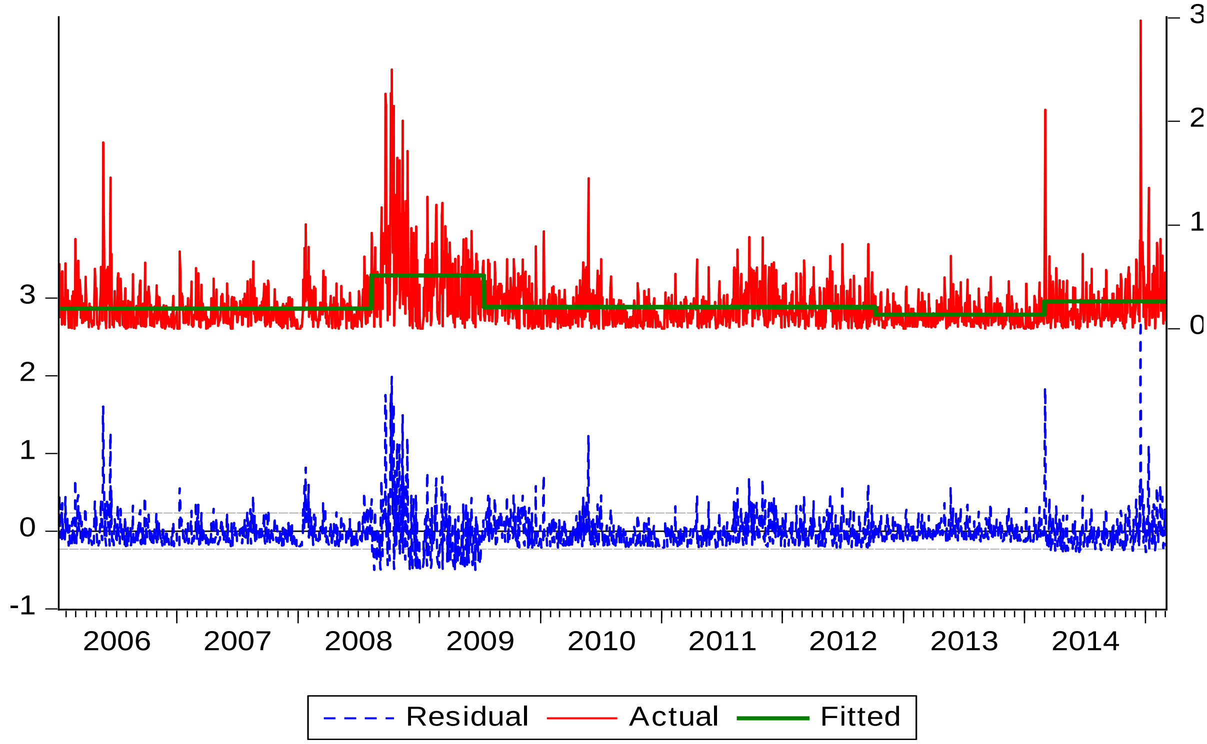


Appendix C Regression output for structural break tests, made by the authors using data from *Thomson Reuters Datastream*

Variable	Break-date	t-Statistic
Volatility Index *RTS*	15 September 2008	40.92337***
	27 February 2009	14.47943***
	02 October 2009	65.75385***
	02 October 2012	40.74966***
	03 March 2014	61.08083***

*** indicate significance of results at 1% significance level.

Appendix D - Historical volatility break-periods, graphical representation, made by the authors using data from *Thomson Reuters Datastream*



Appendix E - Regression output for structural break tests, made by the authors using data from *Thomson Reuters Datastream*

Variable	Break-date	t-Statistic
Realized historical daily volatility (annualized)	08 August 2008	7.7272***
	15 July 2009	17.9267***
	09 October 2012	18.0629***
	28 February 2014	10.4865***

*, ** and *** indicate significance of results at 10%, 5% and 1% significance level, respectively.

Realized historical volatilities were calculated using sample standard deviation for daily returns and afterwards they were annualized by multiplying with square root of trading days of the stock index. 252 trading days are assumed.

Appendix F The selection of the lag length based on the VAR model, made by the authors using data from *Thomson Reuters Datastream*

Panel A. Stable period					
	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Log likelihood	3770.100	3799.438	3798.917	3796.302	3788.271
AIC	-20.4245	-20.5909	**-20.5952**	-20.5880	-20.5509
SBIC	-20.2970	**-20.3675**	-20.2753	-20.1713	-20.0370
Panel B. Crisis Period					
	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Log likelihood	2430.629	2449.485	2445.574	2450.432	2441.837
AIC	-18.5336	-18.6807	-18.6531	**-18.6933**	-18.6291
SBIC	-18.3697	**-18.3931**	-18.2411	-18.15620	-17.9662

Appendix G Johansen cointegration test, made by the authors using data from *Thomson Reuters Datastream*

Panel A. Stable Period						
	No. of int. vectors	Lag	Trace	Critical (at 10%)	Max-eigen.	Critical (at 10%)
Russia, U.S., EU	1	2	35.1339	39.7553	25.3442*	23.4409
Panel B. Crisis Period						
	No. of int. vectors	Lag	Trace	Critical (at 10%)	Max-eigen.	Critical (at 10%)
Russia, U.S., EU	0	2	25.5368	39.7553	14.64859	23.4409

* - indicate significance of results at 10% significance level

Appendix H Cointegrating relationships between *S&P 500*, *STOXX Europe 50* and *RTS* indices, made by the authors using data from *Thomson Reuters Datastream*

Panel A. Stable Period				
	No. of int. vectors	Lag[A]	Trace	Max-Eigen
RTS, S&P 500	1	2	23.6588*	18.2944*
RTS, STOXX Europe 50	1	1	25.4420*	20.8456**
S&P 500, STOXX Europe 50	1	2	22.4249	18.0913*
Panel B. Crisis Period				
	No. of int. vectors	Lag[A]	Trace	Max-Eigen
RTS, S&P 500	0	1	16.6032	11.9797
RTS, STOXX Europe 50	0	1	11.2768	7.2696
S&P 500, STOXX Europe 50	0	2	16.8949	13.3969

*, ** indicate significance of results at 10% and 5% significance level, respectively

[A]- Lag length was determined using Schwarz information criterion for each bivariate VAR model separately. P- values provided by MacKinnon-Haugh-Michelis (1999).

Appendix I Lag length for the VAR and VECM models, made by the authors using data from *Thomson Reuters Datastream*

Panel A. Stable period

	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Log likelihood	3727.878	3739.467	3747.577	3750.007	3751.743
AIC	-20.587	**-20.601**	-20.596	-20.560	-20.519
SBIC	**-20.457**	-20.375	-20.273	-20.140	-20.002

Panel B. Crisis Period

	VAR(1)	VAR(2)	VAR(3)	VAR(4)	VAR(5)
Log likelihood	2378.295	2385.330	2399.779	2401.295	2413.590
AIC	-18.632	-18.617	**-18.660**	-18.601	-18.6267
SBIC	**-18.465**	-18.324	-18.242	-18.058	-17.958

Appendix J Granger causality test, made by the authors using data from *Thomson Reuters Datastream*

Panel A. Stable Period

Null-hypothesis:	F-statistic	Prob	Conclusion
S&P 500 does not cause STOXX Europe 50	-6.1216	0.000	S&P 500 ↔STOXX Europe 50***
STOXX Europe 50 does not Granger cause S&P 500	-4.1287	0.000	
S&P 500 does not Granger Cause RTS	-2.0363	0.043	S&P 500→ RTS**
RTS does not Granger Cause S&P 500	0.1545	0.877	
STOXX Europe 50 does not Granger cause RTS	-4.1287	0.000	STOXX→ RTS***
RTS does not cause STOXX Europe 50	-0.2914	0.771	

Panel B. Crisis Period

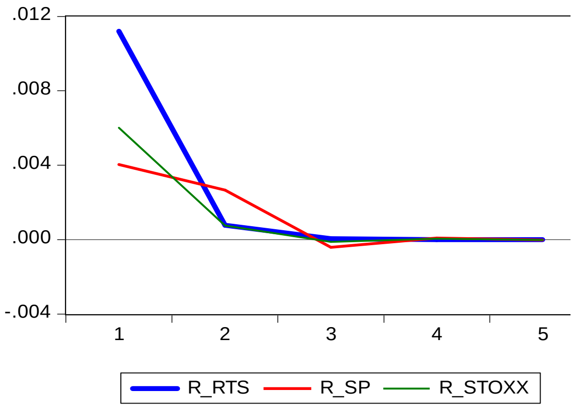
Null-hypothesis:	F-statistic	Prob	Conclusion
S&P 500 does not cause STOXX Europe 50	15.828	0.000	S&P 500 →STOXX Europe 50***
STOXX Europe 50 does not Granger cause S&P 500	0.7838	0.377	
S&P 500 does not Granger Cause RTS	7.7682	0.006	S&P 500 → RTS***
RTS does not Granger Cause S&P 500	0.2089	0.648	
STOXX Europe 50 does not Granger cause RTS	6.5789	0.011	STOXX→ RTS**
RTS does not Granger cause STOXX Europe 50	0.8714	0.351	

*, **, *** - indicate significance of Granger causality linkage at 10%,5% and 1% significance level respectively

Appendix K - Impulse response analysis during the stable period and the Russian crisis periods, made by the authors using data from *Thomson Reuters Datastream*

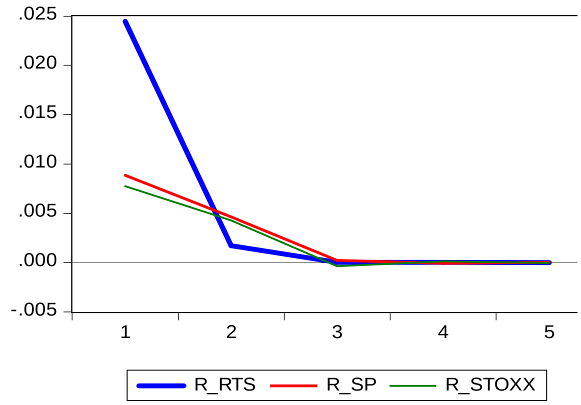
Stable period

Response of R_RTS to Generalized One S.D. Innovations (Plot 1)

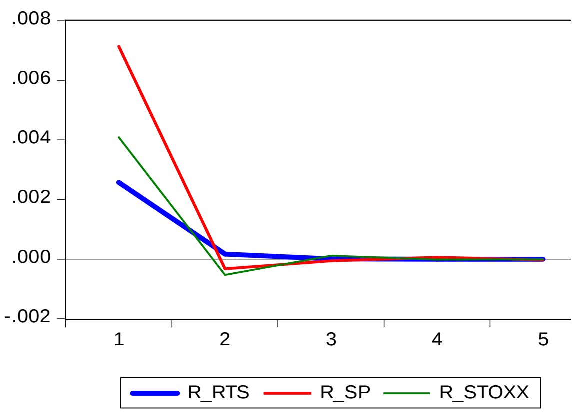


Crisis period

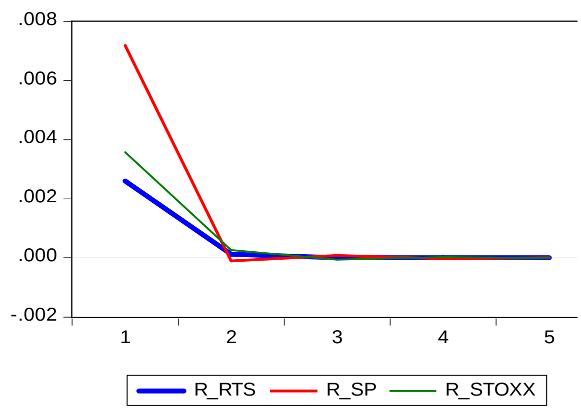
Response of R_RTS to Generalized One S.D. Innovations (Plot 2)



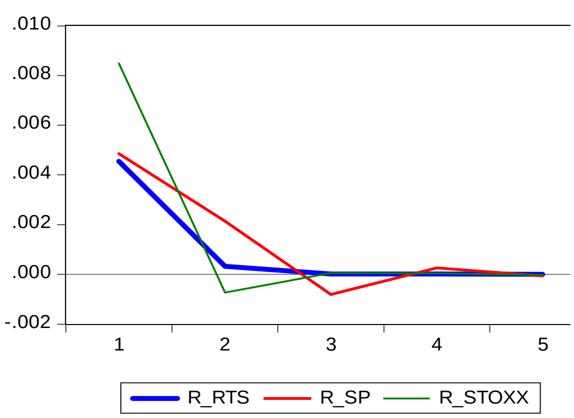
Response of R_SP to Generalized One S.D. Innovations (Plot 3)



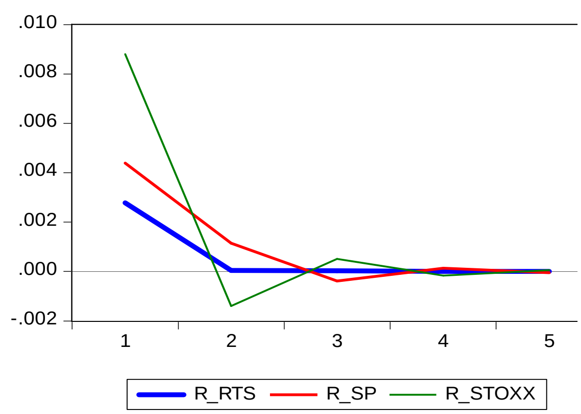
Response of R_SP to Generalized One S.D. Innovations (Plot 4)



Response of R_STOXX to Generalized One S.D. Innovations (Plot 5)



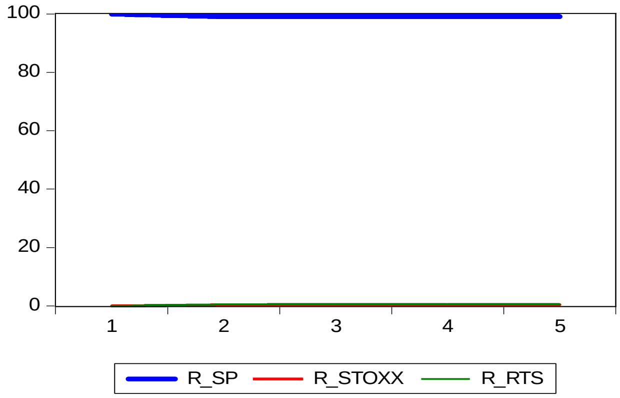
Response of R_STOXX to Generalized One S.D. Innovations (Plot 6)



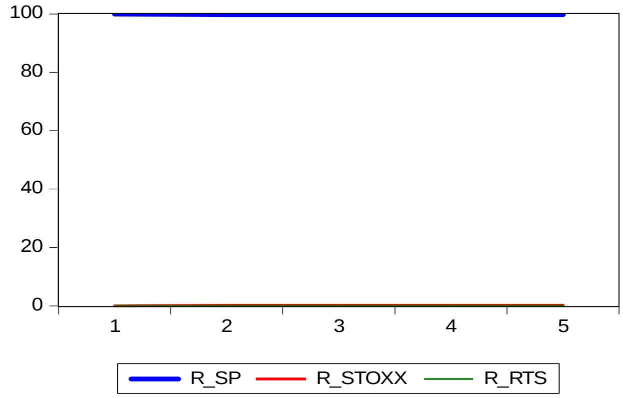
Appendix L - Variance decomposition analysis during the stable period and during the Russian crisis periods, made by the authors using data from *Thomson Reuters Datastream*

Stable period | **Crisis period**

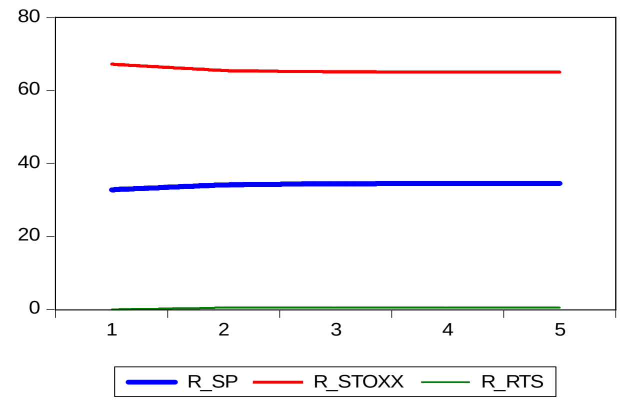
Variance Decomposition of R_SP (Plot 1)



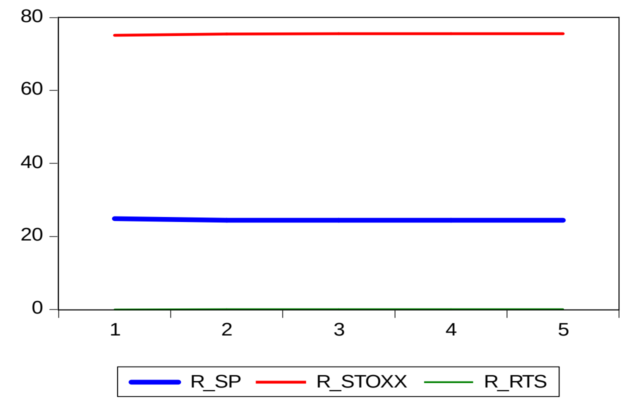
Variance Decomposition of R_SP (Plot 2)



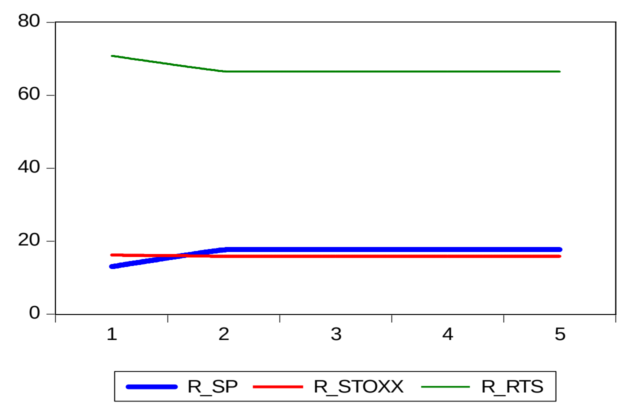
Variance Decomposition of R_STOXX (Plot 3)



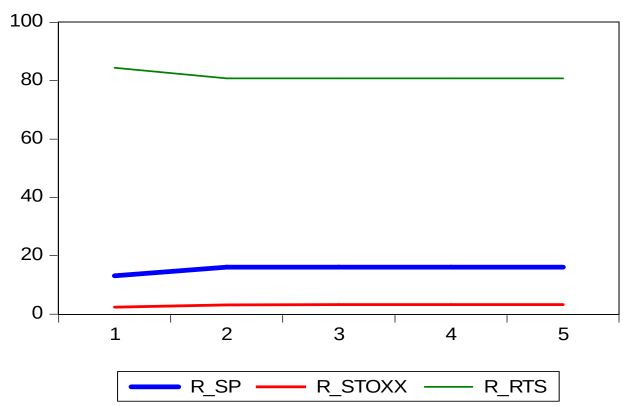
Variance Decomposition of R_STOXX (Plot 4)



Variance Decomposition of R_RTS (Plot 5)



Variance Decomposition of R_RTS (Plot 6)



Appendix M – VAR-BEKK model estimates**,** made by the authors using data from *Thomson Reuters Datastream*

A. Stable Period						
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
	$U.S. (i = 1)$		$EU\ (i = 2)$		$Russia\ (i = 3)$	
$b(i, 1)$	0.00630***	0.00073	0.00000	-	0.00000	-
$b(i, 2)$	0.00485***	0.00006	0.00657***	0.00036	0.00000	-
$b(i, 3)$	0.00418***	0.00069	0.00447***	0.00065	0.00945***	-
$c(i, 1)$	-0.11392	0.11603	0.07741	0.10455	0.16110**	0.07125
$c(i, 2)$	0.01872	0.11167	-0.47211**	0.13721	0.20217**	0.09282
$c(i, 3)$	-0.15095	0.14660	-0.17807	0.16491	0.00601	0.12340
$g(i, 1)$	0.19017*	0.11477	-0.11313	0.15686	-0.21271	0.18241
$g(i, 2)$	0.15041	0.21410	-0.09797	0.07339	-0.16979	0.15751
$g(i, 3)$	0.08122	0.04847	-0.06784	0.13927	-0.09563	0.11277

B. Crisis period						
	Coefficient	Standard error	Coefficient	Standard error	Coefficient	Standard error
	$U.S. (i = 1)$		$EU\ (i = 2)$		$Russia\ (i = 3)$	
$b(i, 1)$	-			-		
	0.00560***	0.00133	0.00000		0.00000	-
$b(i, 2)$	0.00098	0.00393	0.00179	0.00694	0.00000	-
$b(i, 3)$					-	
	0.00048	0.00307	0.00017	0.02357	0.01793***	0.00331
$c(i, 1)$	-0.03373	0.13290	0.17204**	0.07998	0.05629**	0.02783
$c(i, 2)$	-					
	0.57905***	0.11067	0.37697***	0.11380	0.09050***	0.03700
$c(i, 3)$	0.71332	0.46317	0.08572	0.19152	0.37025***	0.07845
$g(i, 1)$	-0.08545	0.27790	0.16781	0.17809	-0.17135	0.11366
$g(i, 2)$					-	
	-0.18427	0.64855	0.33294	0.50104	0.36097***	0.09883
$g(i, 3)$	-0.22277	1.00332	0.42252	0.94774	-0.43915**	0.22067

*, ** and *** denote test statistic significance at 10%, 5% and 1% significance level, respectively

Appendix N – Foreign direct investments from the U.S. to the EU, made by the authors using data from U.S. Department of Commerce (2014)