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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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**CONCEPTS**

- **Dynamic linkage**- In this paper dynamic linkages refer to price, return and volatility transmission linkages among stock markets
- **Short-run dynamic linkage-** linkage between returns of various stock markets
- **Long-run dynamic linkage**- linkage between prices of various stock markets. Also referred as cointegration or co-dependence.
- **Interdependence**- a stable state of dependence between stock markets
- **Integration**- high degree of association among stock markets in the long-run that is not affected by external shocks.
- **Contagion**- increase in shock and volatility dependence between equity markets during a turmoil period compared to their level during a predefined stable period
- **Shocks/innovations-** sudden changes in returns of stock indices

**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 analyzes 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 analyzing 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 tranquility 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.

## 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.

At this point, we can split the relevant literature that analyzes changes in dynamic linkages into two broad groups, one that consists of research papers that analyze stock market interdependence by using short and long-run associations among stock market index series and the other one that is comprised of research papers that analyze the contagion effect by using volatility spillovers. The major purpose of the former literature is to provide some suggestions regarding portfolio diversification strategies and shock transmission channels. On the other hand, the main aim of the studies that form the latter group is to analyze the spread of turbulence during crises among stock markets in order to provide better decision tools in such areas as asset pricing, option pricing, hedging, risk management and portfolio selection. To create a better picture of the previous studies, we will initially review works concerned with analyzing the interdependence of stock markets through short-run and long-run associations and afterwards we will discuss contagion effect and related literature in more depth.

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

### *2.1 Literature on stock market interdependence*

Numerous research papers are concerned with analyzing long-run interdependence among stock markets. After Gruebel (1968) explained the benefits of international portfolio diversification in his study, the long-run relationship among national stock markets has been examined in a series of works such as Lawson et al. (1971), Ripley (1973), Panton et al. (1976) among others. Since the studies of Engle and Granger (1987) and Johansen and Juselius (1990), numerous researches have started to use cointegration hypothesis in order to investigate long-run association among financial markets (Chowdhury, 1994; Masih & Masih, 1997; Taylor & Tonks, 1989). When assessing the linkages among international equity markets, it might be of interest to find out whether there are common forces that impact the long-run movement of prices of stock indices or they are just driven by their own fundamentals. This question might be answered by performing a cointegration analysis. The vast literature on the dependence among international stock markets covers dynamic linkages between equity markets in the long-run and in the short-run. The analysis of the former type of linkage is more relevant for studying long-run gains due to diversification opportunities, while short-run dynamic linkages are examined in order to shed light on the propagation mechanism of international stock market shocks and causality dynamics linkages between returns of different stock markets.

At this point, we would like to separate the literature on interdependence into two major categories: the first category includes paper examining interdependence in order to suggest investment, diversification and risk-hedging opportunities, while the second category is mainly concerned with the impact of turmoil periods on the interdependence linkages between a set of countries. Some examples of reputable research papers from the first category are as follows:

Glezakos et al. (2007) investigated short and long-run interdependence between the Greek and developed equity markets during 2000 to 2006. The authors found that the long-run and short-run dynamic linkages among analyzed financial markets are strengthened over the analyzed time period, thus there are less diversification opportunities. The U.S. global influence was found to be noticeable on all major world financial markets. Their findings also suggest that the Athens stock market is strongly affected by the U.S. and the German markets, but the influence is very short lasting.

Stikauth (2012) studied integration between Indian and several different Asia-Pacific equity markets from the beginning of 2000 till 2010. By using a Vector Error Correction model, the author exhibited that in short-term the deviation from the long-term equilibrium can be up to 25%. Also decomposing Indian equity market variance, Strikauth explored that the neighboring equity markets considerably contributed to the variance of the Indian equities. In addition, using the same methodology as Chittedi (2010), the author proved that the Indian stock market is cointegrated with the Asia-pacific region equity markets; therefore, there are fewer diversification opportunities.

Jebran (2014) studied dynamic linkages between South Asian equity markets. He used monthly closing prices between November 2003 and November 2013. After performing the Granger causality test, he concluded that returns of the Indian, Indonesian and Malaysian stock markets unidirectionally Granger cause the returns of Sri Lanka's stock market. Further, by undertaking Johansen's cointegration test, it was found that Sri Lanka's and Indonesian markets are co-dependent of one and other in the long run; therefore, the long-run benefits from hedging and diversification cannot be acquired.

As we mentioned above, another important domain of research papers is the one in which authors analyze the impact of equity market crashes on the interdependence among equity markets. The 1987 international stock market collapse and the 1997-1998 global emerging market crises have created a debate on how financial crises affect linkages between different international capital markets.

Yang, Kolari & Min (2003) examined long-run relationships and short-run dynamic causal linkages among the U.S., Japanese, and Asian emerging stock markets during the 1997-98 Asian financial crisis. Their results indicate that both long-run cointegration relationships and short-run causal linkages among these markets were strengthened during the crisis. Also their results suggest that the analyzed countries became more cointegrated after the crisis than they were before it. These findings indicate that the degree of interdependence among equity markets varies over time and it is substantially affected by financial crises.

Yang, Hsiao, Li & Wang (2006) examined the long-run price linkage and dynamic price transmission among the U.S., German, and four Eastern European markets after the 1998 Russian financial crisis. Their results suggest that both price linkage and the dynamic price transmission were strengthened by the crisis. The global influence of the U.S is significant on all the Eastern European markets only after the crisis but not before.

Herwany and Febrian (2013) studied long and short-run linkages between the Indonesian financial sector and the equity markets of the U.S., the UK and four Asian countries before and during the sub-prime crisis. The authors used cointegration and Granger Causality tests to show that all the markets were cointegrated prior to the crisis and that the sub-prime crisis did not distort the long-run linkage among them. In addition, they found that there were short-run diversification benefits between analyzed stock markets.

Lee and Jeong (2014) examined the impact of global financial crisis on the level of stock market cointegration. They researched the dynamic movement of two regional equity markets, North Asia and Europe, during the period of 1 January 2000 and 31 December 2012. The authors found that the Northeast Asian equity market remained independent from the European and global stock market movement during the analyzed period. Also, they suggested that the level of long-run linkages between the European and global stock markets had temporally increased during the global financial crisis; however, the level returned to its pre-crisis value after the market crash period.

Inder (2014) studied stock market interdependence between Indian and eight other Asian stock markets. The author employed Johansen's cointegration test and Granger Causality test for the time period between early 2001 till mid-2013. The results showed that Indian equity market became more cointegration during the post subprime crisis period with other Asian stock markets than it was during the pre-crisis period, thus the diversification benefits are diminished. The only exception is India's integration with Japanese equity markets where the level of integration did not change after the crisis. In the short-run the Granger causality test predicted that Asian stock markets do not Granger cause Indian stock market.

In summary, the researches regarding stock market interdependence covers two avenues: (1) portfolio diversification and risk hedging opportunities over long time periods, and (2) changes in equity market dependence during periods of financial turmoil. The main findings regarding the initial pillar are as follows. First, the long and short-run dependence between equity markets increases over time. Second, the deviations from the long-run equilibrium can substantiate to 25%, thus in some cases investors can reap short run benefits from diversification. The key takeaways from the second pillar are as follows. Dependence between equity markets is time-varying and increases during periods of high uncertainty. Typically, the level of co-dependence is higher after the crisis than before the financial turmoil. Thus, both pillars lead to the conclusion that in the majority of the cases the benefits of international diversification decreases.

### *2.2 Literature on contagion*

Regarding the analysis of contagion, a large number of definitions and opinions can be found in the literature (Forbes & Rigobon, 2002; Kasinomics, 2008; Masson, 1998). Contagion is described by Masson (1998) as "*monsoonal effects*", where he suggests that major economic shifts in industrial countries can create crises in emerging countries, while "spillovers" are regarded as a consequence of the interdependence among countries. He considers that pure contagion is related to investors' expectations, which are not linked to a country's macroeconomics fundamentals. Bekaert, Harvey & Ng (2005) define contagion as an excess correlation between markets, more than it can be explained by economic fundamentals.

The World Bank (Kasinomics, 2008) suggests three definitions of contagion:

- Broad definition: "Contagion is the cross-country transmission of shocks or the general cross-country spillover effects."
- Restrictive definition: "Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks."
- Very restrictive definition: "Contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "tranquil times."

From the above-mentioned definitions we can conclude that there is a lack of agreement on how contagion should be defined and whether the transmission of shocks through economic fundamentals should even be considered as contagion. In anticipating changes in macroeconomic fundamentals of other countries, financial markets respond and reach a new equilibrium; however, as Moser (2003) suggests, stock markets do not cause the change in the equilibrium of macroeconomic variables. When a country faces a shock, other countries will fine-tune their real and financial variables to reach a new equilibrium, thus undergoing internal shocks. Shocks are consequences of normal dependence between stock markets. Capital markets do not cause shocks, but they spread them and speed up their transmission. In this paper we will use the World Bank's very restrictive definition of contagion, which was also used in similar studies by Bekaert, Harvey & Ng (2005) and Trenca and Dezsi (2013). This definition states that contagion is considered as an excess correlation between stock markets during a crisis period compared to a period of tranquility, where excess correlation represents an increase in dependence of the capital markets.

In order to analyze or speculate about contagion transmission mechanisms, a distinction should be made between channels of contagion acting in interdependent markets and channels attributed to investor behavior. In interdependent markets the possible channels of spreading contagion are common shocks, trade linkages, competitive devaluations and financial linkages (Trenca, Petria & Dezsi, 2013). Engle (2009) suggested that another channel of contagion, in addition to the one related to interdependent equity markets, is the one linked to investors' behavior and can be explained by the portfolios that they trade within multiple stock markets. "The concerns about contagion are generally founded on the idea that there is something different about extremely bad events that leads to irrational outcomes, excess volatility and even panics. In the context of stock returns, this means that if panics grips investors as stock returns fall and ignore them economic fundamentals, one would expect large negative returns to be contagious in the way small negative returns are not" (Bae, 2003, p.718-719).

The empirical studies on financial contagion are numerous and below we will refer only to some of them which examine contagion effects during some well-known crisis periods.

Yang and Bessler (2004) analyzed the stock market crash in 1987. Using directed analytic graphs (DAG) and Structural Vector Autoregressive (SVAR) modeling they proved that the crisis in 1987 originated in the U.S. and spread to the UK, Australia, Germany, and other developed markets despite no change in underlying macroeconomic variables. An interesting addition is that the Japanese market alleviated the downfall in the U.S. market and sped up America's recovery.

Chancharoenchai and Dibooglu (2006) used a Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH) model to investigate volatility spillovers in six Southeast Asian stock markets around the Asian crisis from 1997. Particularly, they used a bivariate GARCH-M model to analyze the behavior of individual markets and their interactions with other regional markets. Their results suggest that the "Asian contagion" started in Thailand and was transmitted to other regional and global markets.

Even though the extensive literature has found contagion during the crises from 1990s, there is little evidence of contagion during the Argentinian (2001-02) crisis and the Turkish crisis (2001) (Claessens & Forbes, 2004).

Using a bivariate GARCH-BEKK model, Abbes (2013) found that the volatility of the U.S. stock market was transmitted to Asian and European financial markets during the 2008 subprime crisis. In addition, the author found that the cross-country residual correlation between the U.S., European and Asian stock markets increased during the turmoil period as compared to the tranquil period, suggesting that contagion effect took place between the analyzed countries during the 2008 global financial crisis.

Li (2009) compared the contagion effect from the 1987 U.S. stock market crash, 1994 Mexico Peso crisis, 1997 East Asian crisis and the subprime crisis, which was ongoing at the time he performed his research, on the Canadian banking sector. The author used two different time periods for the subprime crisis period in order to prove the persistency of the contagion effect. In both cases the author, using Kendall's tau measure, found a significant and persistent contagion effect from the U.S. to Canada. Castellanos (2012) also studied the sub-prime crisis, in particular the short and the long-run effects on different developed markets. Castellanos used a data set with varying time frames and concluded that the longer the time period under scrutiny, the more homogenous are the co-movements. Thus, it is possible to observe a contagion effect at different points in time in an ongoing crisis.

To summarize, contagion is an increase in correlation between stock markets during a crisis. It can spread through trade linkages, competitive devaluations, financial linkages and changes in investors' behavior. It can be determined by using various ARCH family models and one can observe it in most of the market crashes: 1987 crisis, Asian crisis in 1997 and 2008 sub-prime crisis. In addition, it is possible to observe it during an ongoing financial turmoil.

### *2.3 Interdependence and contagion: The case of Russia*

Despite the vast literature on contagion and interdependence of international stock markets, the literature regarding Russian financial market interdependence and its contagion effects to other markets is very limited. Some of the most important research papers that touch upon the issues are listed as follows:

Peresetsky and Ivanter (2000) studied the pattern of long-term association of the Russian financial market with other international capital markets, namely with capital markets of the U.S., Japan and Europe by using cointegration analysis. After investigating daily returns of the MICEX index during the period ranging from 1996 until 1997, the authors concluded that the Russian stock market became increasingly integrated with the world financial markets. In addition, they found that the August 1998 crisis weakened the integration of the Russian stock market with other global equity markets, a result which cannot be explained by a contagion effect.

Empirically examining the episodes of significant turbulence in the global financial markets during 1998 by using a univaritate GARCH model, Fry et al. (2002) found that there were substantial international contagion effects towards global capital markets resulting from the Russian crisis.

Anatolyev (2008) analyzed weekly Russian stock market data for two periods: from January 1995 to January 2005 and from January 1999 to 1 January 2005 (i.e post 1998 Russian crisis period only) using Johansen cointegration approach. His results suggest that the interdependence of the Russian and European stock markets is higher than the interdependence between the Russian capital market and the U.S. or Asian markets during the post-crisis period.

Aktan et al. (2009) investigated the linkages among stock markets of Brazil, Russia, India, China, and Argentina (BRICA) and the U.S. They employed the Vector Autoregressive (VAR) technique to model interdependencies and Granger-causality to find short-run linkages among above-mentioned markets. In addition, they used impulse response test to evaluate the persistence of stock market shocks using daily data from 1 January 2002 to 18 February 2009. The authors found that the most integrated markets among BRICA countries are Russia and Brazil. The results of their Granger causality test suggest that Russia impacts all four other countries. Impulse response tests results indicated that all countries respond to an anticipated shock immediately and recover in five or six days.

Using a multivariate GARCH-BEKK model Khan (2010) analyzed volatility spillovers between Russia, the U.S. and Europe during the 2008 global financial crisis and found evidence of strong bidirectional return and volatility linkages between the sample countries.

Chittedi (2010) researched the U.S., UK, and Japan’s stock market integration with the equity markets of the BRIC countries. The author employed Johansen’s cointegration test. He found that by investing in these particular markets, an investor can reap cross-market diversification benefits. To analyze short-run relationship among the previously mentioned markets, the author used a Vector Error Correction Model (VECM) and concluded that equity markets of the U.S. and China dominate the equity markets of the UK and that of the BRIC countries, and when the long-run equilibrium is distorted the UK and BRIC countries’ stock markets have to adjust to the long-run equilibrium.

Korhonen and Peresetsky (2013) examined interdependence between Russian, some Eastern European stock markets and capital markets of developed countries such as the U.S., Japan and Germany during the period from 2000 to 2012 using a TGARCH-BEKK model. Their results suggest that a high level of interdependence between all the analyzed markets is reached, thus the authors advocate that a substantial increase in the integration among Russia and other analyzed countries is unlikely during next years.

Joshi (2014) analyzed volatility spillover among BRIC stock markets using a GARCH-BEKK model for the time period between 1 January 2009 and 1 June 2014. He found evidence of bi-directional shock spillover among Brazil and Russia, Russia and China and Russia and India. In addition, he found a bi-directional volatility spillover between Russian and Brazilian stock markets.

In essence, the interdependence between Russian equity market and other global capital markets decreased during the Russian crisis in 1997-98. This crisis was contagious, as part of volatility was transmitted from Russia to equity markets all over the world. The subprime crisis led to stronger long-run linkages between Russian and other international stock markets. Furthermore, the 2008 global financial crisis exhibited bidirectional volatility spillover between Russia, the U.S. and the EU. Finally, it is considered that due to the already high level of integration, it is unlikely that Russian capital market will become more integrated with the rest of the world.

### *2.4 Russian crisis*

The most recent turbulent period of significant importance is the Russian financial crisis that started in 2014 (Ginsburg, 2014). This crisis weakened Russia's economic stability severely. It is not only financial magazines saying that Russia undergoes a financial crisis (Ginsburg, 2014; Korsunskaya, Kelly & Golubkova, 2014; Shatalova, 2014), but also the president of Russia, Vladimir Putin, who used his end-of-the-year news conference to blame Western sanctions for "Russia's financial crisis" (Kottasova, 2014).In addition, IMF (2015) forecasts are quite pessimistic, suggesting that Russia's GDP is going to contract by 3% in 2015 and by additional 1% a year later. Some causes of this crisis are considered to be the substantial depreciation of the Russian ruble relative to other currencies and stagnation of the Russian economy (Katz, 2014). The ruble depreciated due to the decrease of investors' confidence in the Russian economy, encouraging them to sell their Russian assets; therefore diminishing the demand and the price of the Russia's currency (Kitroeff & Weisenthal, 2014). The three major factors that are considered to have contributed to the decrease in investors' confidence are the slump in the global oil prices, which dropped by around 50% in 2014 (Friedman, 2014; Lawler, 2014), the international sanctions imposed on Russia after it annexed Crimea and intervened in the Ukrainian conflict (Grove & Strobel, 2014; Kitroeff & Weisenthal, 2014), and the retaliatory sanctions of Russia on the western world (Tomlinson, 2014).

During the first round of sanctions that were enacted in the wake of the annexation of Crimea by the Russian Federation, the U.S. and the EU prohibited their citizens to have any business deals with a number of Russian and Ukrainian sanctioned individuals and companies (Meltzer, Bourgeois & Carroll, 2014). After the second round of sanctions, they have extended the list of sanctioned individuals and companies (Council of the European Union, 2014; Reuters and Associated Press, 2014). The third round of sanctions was more punitive. On 17 July 2014, the United States expanded its transactions ban to other major Russian companies (Razumny, 2014), while on 25 and on 30 of July, the EU expanded its sanctions to additional individuals and entities (Council Implementing Regulation, 2014a). Soon afterwards, the EU enacted additional sanctions against certain sectors of Russia's economy (Council Implementing Regulation, 2014b). Russia, on 7 August 2014, in retaliation to western sanction, imposed a ban on the U.S. and the EU agricultural goods (Tomlinson, 2014).

In addition to having a negative effect on consumers and on companies, the crisis has been detrimental to financial markets. For example, on 16 December 2014, the *RTS* index, which is a free-float capitalization-weighted index of the 50 biggest Russian stocks traded on the Moscow Exchange and which is calculated in the U.S. dollars, dropped by 12%, thus registering the biggest daily decrease since the global financial crisis of 2008 (Galouchko & Doff, 2014).

The triggers of the Russian crisis are considered to be the conflict between Russia and Ukraine over Crimea and the sanctions which were later imposed on and by Russia. Some of the important dates which can denote the starting date of the crisis are 28 February, 5-6 March and 17 March. The first date is considered to be the date when the Russian Foreign Ministry officially admitted that Russian forces seized Crimea (Ensor & Merat, 2014; Hufbauer, Cimino & Moran, 2014). The latter two dates are the dates when the U.S. and the EU authorized and respectively imposed the first round of sanctions against Russia (Hufbauer, Cimino & Moran, 2014; Kini, Micarelli & Gladstone, 2014). Even though the initial sanctions against Russia were minimal and one might argue that they were not likely to lead to an economic crisis, an important aspect to consider when making such statements is the decline in investor confidence, which can have quite substantial economic outcomes. For example, the net outflow from Russia in the first quarter of 2014 was $64 billion, which is higher than Russia's net capital outflow throughout whole 2013 (Bush, 2014). Lower investor confidence can also have significant adverse effect on financial markets due to higher risk premium that investors attach to stocks. In Russia, *RTS* equity index dropped by more than 10% during the beginning of January until early May (Hufbauer, Cimino & Moran, 2014).

We believe that the Russian crisis, which started in 2014, might have been contagious to other stock markets. According to the contagion transmission mechanisms described by Trenca, Petria & Dezsi (2013) and taking into account that Russian stock market is not independent, but rather interdependent (Korhonen & Peresetsky, 2013; Peresetsky & Ivanter, 2000), the transmission of contagion could be propagated through the oil price shock and/or the plummeting ruble exchange rate. Another possible avenue for the transmission of contagion might be the deteriorating trade linkages between Russia and other countries that might have an impact on the balance of payments and other fundamental variables through lower demand for imports (Worstall, 2014). This leads to a reduction in expo*rts* and income to Russia's trade partners.

In sum, Russia's financial crisis started in early 2014 with the conflict in Ukraine. The factors that increased the intensity of the crisis are the depreciation of the ruble, 50% drop in the oil price, international sanctions levied on and by Russia and the decline in investors' confidence. As Russia's equity market is co-dependent and it has recently experienced a turbulent period, there is a possibility that this recent crisis was contagious to other markets. According to the existing literature, the contagion could have spread through the crude oil market, exchange rate market, deteriorating trade linkages or change in investors' behavior (see Section 2.2).

### *2.5 Purpose and research questions*

As stated in the previous sections, crises can have a significant impact on the interdependence among stock markets (see Section 2.1). 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.

# 3 METHODOLOGY

This paper is devoted to analyzing changes in dynamic linkages between Russian, U.S. and EU stock markets due to the recent Russian crisis. We will perform the following econometric tests: Bai-Perron structural break, unit-root, cointegration, Granger-causality, variance decomposition, impulse response and a multivariate GARCH model. 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. Unit-root tests are carried out in order to scrutinize whether the times series data is stationary; this test is a premise for other techniques. 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.

The above-mentioned tests and models were estimated using STATA, EViews and R statistical packages.

## *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. This methodology involves regressing a variable of interest on a constant and then testing for changes in that constant during different sub-sample periods. The estimation procedure in our case is executed on the volatility index of the Russian stock market, namely the *RTS Volatility* Index. In general this particular test will show the periods of sudden changes in the average volatility (risk) of the Russian stock market. Similar approach was used by Heinonen (2013) to determine the starting date of the global financial crisis. Bai-Perron test in our paper is based on an information criterion in the context of equal-weighted (UD max) "*Global m breaks versus none*" procedure, which allows us to estimate the timing and number of breaks in data series, given that the maximum number of the possible breaks is pre-specified. The null hypothesis of no structural breaks is tested against a certain number of breaks. In our case, the Bai and Perron regression equation can be defined as follows:

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

where $\sigma_t$ is the *RTS Volatility Index* at time t, $\theta_j$ is the mean of the volatility in the $j'th$ regime, where $j = 0, \dots, m$; $\varepsilon_t$ is the error term. The parameter m is the number of breaks. For a test of the null hypothesis of no breaks against an alternative of m breaks, the "*Global m breaks versus None"* method uses F-statistic to evaluate the following hypotheses (Bai & Perron, 2003):

$$\mathbf{H_0}: \theta_0 = \theta_1 = \cdots = \theta_{m+1}$$

$$\mathbf{H_1}: \exists\ i \in \{0,1,\dots,m+1\}\ and\ j \in \{0,1,\dots,m+1\}\backslash\{i\}, \theta_i \neq \theta_j$$

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 Unit root test*

A unit root test is a statistical test for the proposition that in an autoregressive time series model the autoregressive parameter is one. The test checks for stationarity of the series. Some works of major significance on testing for unit root in time series include that of Dickey and Fuller (1979, 1981). If the variables in the regression model are not stationary, it can be shown that standard assumptions for asymptotic analysis will not be valid. In other words, "t-ratios" will not follow t-distributions; therefore, hypothesis tests and regression parameters will be inaccurate. Despite this issues related to non-stationary series, one can use only unit root data of different stock market indices to find the degree of cointegration between them, since cointegration tests require that data is non-stationary.

Stationary time series have constant mean, variance and covariance over time. Nonstationary time series have time-varying mean or variance or both. If a time series is nonstationary, then one can analyze the series during the period under consideration, but his results cannot be generalized to other time periods.

We used Augumented Dickey-Fuller (ADF) and KPSS tests to check for unit root in data series. If the natural logarithm of the stock index price series is non-stationary, we will use price series to run cointegration analysis. Afterwards, in order to see the level of integration we will run the same tests on the first difference of the logarithmized stock price data (return series).

### 3.2.1 Augmented Dickey-Fuller test

There are three possible versions of the Augmented Dickey-Fuller (ADF) test that are used to check data series for the presence of unit roots.

1. Test for unit root without drift and without trend

$$\Delta \boldsymbol{y_t} = \boldsymbol{\alpha^* y_{t-1}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{\alpha_i} \Delta \boldsymbol{y_{t-i}} + \boldsymbol{\varepsilon_t} \tag{2}$$

2. Test for unit root with drift

$$\Delta \boldsymbol{y_t} = \boldsymbol{\beta_0} + \boldsymbol{\alpha^* y_{t-1}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{\alpha_i} \Delta \boldsymbol{y_{t-i}} + \boldsymbol{\varepsilon_t} \tag{3}$$

3. Test for unit root with drift and deterministic trend

$$\Delta \boldsymbol{y_t} = \boldsymbol{\beta_0} + \boldsymbol{\alpha^* y_{t-1}} + \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{\alpha_i} \Delta \boldsymbol{y_{t-k}} + \boldsymbol{\beta_1 t} + \boldsymbol{\varepsilon_t} \tag{4}$$

where $y_t$ is the observation at time $t$ of the variable that is tested for unit root. $\beta_0$ is the drift term, $t$ is the linear trend term and $\varepsilon_t$ is the error term. Hypotheses of ADF can be stated as follows:

$\mathbf{H_0}$: $\alpha^* = 0$ (Non-stationary)

$\mathbf{H_1}$: $\alpha^* < 0$ (Stationary)

The null hypothesis suggests that the series contains a unit root and is, therefore, a non-stationary process. To test for unit root we have to compute t-statistic $t = \frac{\alpha^*}{\sqrt{var(\alpha^*)}}$ and compare it to the corresponding critical value at different significance levels. If the null hypothesis is rejected, we conclude that the series $y_t$ does not include a unit root.

To perform the Augmented Dickey-Fuller (ADF) tests, it is necessary to specify whether the regression will include a constant, a constant and a linear trend, or neither. One idea would be to run a test with both a constant and a linear trend, because other instances are just special cases of a more general specification. One drawback of this idea is that including irrelevant regressors reduces the power of the test to reject the null hypothesis of non-stationarity. One solution to this issue is to base the equation of the regression on the graphical representation of the series (Verbeek, 2004). If the graph for the data does not start from the origin, then the regression equation includes a constant. If the plot of the data indicates a certain upward or downward trend, then the trend term should be added to the regression.

In addition, it is important to choose the optimal number of lagged difference terms *k*. Choosing too few or too many lags might lead to rejecting the null-hypothesis of unit root when it is true or reducing the power of the test. One idea is to base the decision of the number of lags on Information criteria such as the Schwartz- Bayes information Criterion (SBIC) or Akaike Information Criterion (AIC). Basically it is necessary to choose the optimal lag length that minimizes the information criteria. In our analysis will rely on the SBIC information criterion, because on average it picks a more parsimonious model than the one that AIC suggests (Kočenda & Černý, 2007).

The main limitation of the Augmented Dickey-Fuller (ADF) test is that the power of the test is very low if the process is almost non-stationary. This suggests that the tests will have little power to differentiate between a near unit root and a unit root processes. In addition, the power of the test with a trend variable is lower than the power of a more general model (Brooks, 2002).

**3.2.2 KPSS test**

The KPSS test can be used to avoid the limitation of the low power of the ADF unit root test (Kwiatkowski et al., 1992). According to this test, a series is stationary under the null-hypothesis, while the alternative hypothesis is that that the series has a unit root. The KPSS test is a Lagrange multiplier test and its regression model has only two specifications: it can include an intercept or an intercept and a linear trend $t$. After estimating the regression model, OLS residuals $\varepsilon_t$ are used to compute partial sums $\mathrm{S_t} = \sum_{i=1}^{t} \varepsilon_i$ for all $t$ observations. The test statistic is calculated according to the following formula:

$$\boldsymbol{KPSS\ LM} = \sum_{\boldsymbol{t=1}}^{\boldsymbol{T}} \frac{\boldsymbol{S_t^2}}{\boldsymbol{\hat{\sigma}_\varepsilon^2}} \tag{5}$$

where $S_t = \sum_{s=1}^{t} \varepsilon_s$ and $\hat{\sigma}_\varepsilon^2$ is the estimated error variance of the regressions

$$y_t = \alpha + \varepsilon_t \text{ or } y_t = \alpha + \beta t + \varepsilon_t$$

As a robustness check, we use the ADF and KPSS tests jointly. The results of these two tests can be compared to see whether the same conclusion is reached. If these two tests provide contradictive results, the results of the KPSS will have a higher priority due to the fact that it solves some of the drawbacks of the ADF.

### 3.3.1 Vector autoregressive (VAR) model

Vector autoregressive (VAR) models were proposed by Sims (1980) and can be used to capture the dynamics and the interdependency of multivariate time series. It can be considered a generalization of a system of autoregressive regression models.

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:

$$\boldsymbol{Y_t = C + \sum_{i=1}^{p} A_i Y_{t-1} + \Psi D_t + \varepsilon_t, \quad t = 1, \dots, T,} \tag{6}$$

Where $A_i$ is an $(nxn)$ coefficient matrix and $\varepsilon_t$ 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. Since we examine the changes in linkages among three markets (Russia, the U.S and the E.U) we will have to perform a trivariate VAR model. Such a model with 1 lag and no deterministic variable can be depicted as follows:

$$\begin{pmatrix} \boldsymbol{y_{1,t}} \\ \boldsymbol{y_{2,t}} \\ \boldsymbol{y_{3,t}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{c_1} \\ \boldsymbol{c_2} \\ \boldsymbol{c_3} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\pi^1_{11}} & \boldsymbol{\pi^1_{12}} & \boldsymbol{\pi^1_{13}} \\ \boldsymbol{\pi^1_{21}} & \boldsymbol{\pi^1_{22}} & \boldsymbol{\pi^1_{23}} \\ \boldsymbol{\pi^1_{31}} & \boldsymbol{\pi^1_{32}} & \boldsymbol{\pi^1_{33}} \end{pmatrix} \begin{pmatrix} \boldsymbol{y_{1,t-1}} \\ \boldsymbol{y_{2,t-1}} \\ \boldsymbol{y_{3,t-1}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon_1} \\ \boldsymbol{\varepsilon_2} \\ \boldsymbol{\varepsilon_3} \end{pmatrix} \tag{7}$$

VAR models enable analyzing multiple time series, since they do not require specifying which variables are endogenous and which are exogenous; however, VAR models have some drawbacks. First, 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. Finally, it is not easy to determine the appropriate lag length in a VAR model.

To choose the optimal lag length, two methods are commonly applied. One of them is the likelihood ratio (LR) and another one is the information criteria, such as Akaike (AIC) and Schartz Bayesian Information Criteria (SBIC). The best model is the one that either maximizes LR or the one that minimizes information criteria. Out of these two methods, information criteria model is more powerful (Brooks, 2002). Out of the two specifications of the information criteria method we prefer the SBIC specification because it is more parsimonious, while the AIC will choose on average a model with too many lags.

### 3.3.2 Vector Error Correction Model (VECM)

As it was mentioned above, analyzing multiple time series that are non-stationary using a VAR model is inappropriate and it is required that the unit root series be transformed into stationary series. In case the relationship between initial variables is important to analyze, then simply taking first difference of the non-stationary variables is inappropriate, because it makes impossible to examine the long-run relationship between initial variables (i.e. that is because no long-run solution would exist after such a transformation). Fortunately, using the VECM model one can solve this issue. Therefore, the $VAR(p)$ model is transformed into a Vector Error Correction Model (VECM), so that the stationary differences of the analyzed variables are included in the model instead of the original non-stationary variables. Taking into account the $VAR(p)$ equation which we wrote in the previous sub-section (see equation 6), our VECM model looks as follows:

$$\Delta \mathbf{Y_t} = \mathbf{C} + \Pi\, \mathbf{Y_{t-1}} + \sum_{\mathbf{i=1}}^{\mathbf{n-1}} \Phi_{\mathbf{i}} \Delta \mathbf{Y_{t-i}} + \boldsymbol{\Psi} \boldsymbol{D_t} + \boldsymbol{\varepsilon}_{\mathbf{t}} \tag{8}$$

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

### *3.4 Cointegration test- Johansen approach*

The concept of cointegration was developed by Engle and Granger (Engle and Granger, 1987). If two or more series are non-stationary (have a unit root), but a liner combination of them is stationary, then the series are referred to as cointegrated.

In order to investigate *long-run relationship* between variables in multivariate models, we will use the Johansen cointegration test (Johansen, 1991). In comparison with the Engle-Granger approach, this technique can identify more than one cointegrating relation among the analyzed variables. The core of the Johansen method relies on testing for cointegration by looking at the rank of the $\Pi$ matrix via its eigenvalues (characteristic roots). The eigenvalues depend on the form of the VEC model and on the composition of its deterministic terms. The method deduces the number of cointegration rank by determining the number of eigenvalues that are statistically different than 0, and then estimates the model under the rank constraints.

Let us consider a variable *r*, which can be defined either as the number of linearly independent combinations of the variables in $Y_t$ or as the rank of the matrix $\Pi$ from the equation 8. If *r* is equal to $n$ (the number of column vectors of $Y_t$ ), then the matrix $\Pi$ is full rank. If $\Pi$ is less than full-rank, it can be written as $\Pi = a * \beta'$, where both $a$ and $\beta$ are $(nxr)$ matrices.

Therefore, the coefficient matrix $\Pi$ is a product of $\alpha$ and $\beta$ matrices, where $\alpha$ indicates the speed of adjustment to equilibrium, while $\beta$ is interpreted as a long-rung relationship between the levels of the analyzed variables.

### 3.4.1 Testing for the rank of $\Pi$ matrix

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

$$\text{Trace statistics: } \boldsymbol{\lambda_{trace}(r_0) = -T \sum_{i=r_0+1}^{n} \ln\left(1-\hat{\lambda}_i\right)} \tag{9}$$

where $r_0$ is critical number of cointegrated vectors against which the hypothesis is being tested; $i = r_0 + 1, r_0 + 2, \dots, n$; T is sample size and $\lambda$ denotes eigenvalues. The tested null and alternative hypotheses are as follows:

$$\mathbf{H_0}: \mathrm{r} \le r_0$$

$$\mathbf{H_1}: r_0 < r \le n$$

The trace test checks or the smallest $(n - r_0)$ that is significantly different than zero, where $n$ is the number of column vectors of $Y_t$. Alternatively, the maximum eigenvalue test can be performed. This test is based on the $(r_0 + 1)'th$ largest eigenvalue:

$$\text{Maximum eigenvalue statistics: } \boldsymbol{\lambda_{max}(r_0, r+1) = -T ln(1 - \lambda_{r_0+1})} \tag{10}$$

The tested null and alternative hypotheses for maximum eigenvalue statistic are:

$$\mathbf{H_0}: \mathrm{r} \le r_0$$

$$\mathbf{H_1}: \mathrm{r} = r_0 + 1$$

Luutkepohl, Saikkonen & Trenkler (2001) found that there is a slight difference between these two statistics in the case when the sample size is small. After applying Monte Carlo simulation in order to compare trace statistic to maximum eigenvalue statistic, they found that the power of trace tests in small samples (≤100 observations) is slightly superior to the power of eigenvalue tests. In particular, it is suggested that trace tests are advantageous if there at least two more cointegration relations in the process than specified under the null-hypothesis. Taking into account that the data samples on which we perform cointegration analysis are at least twice as large as the minimum sample size mentioned above and considering that we might have rather few potential cointegration relations, maximum 3, we do not prefer one statistic over the other, but we will consider the results of both of them while drawing our conclusions.

### 3.4.2 Selection of the deterministic components in the Johansen test

Assuming that k=2 and $D_t = t$ we can rewrite equation 8 as:

$$\Delta\mathbf{Y_t} = \mathbf{C} + \boldsymbol{a\beta}'\mathbf{Y_{t-1}} + \Phi_1\Delta\mathbf{Y_{t-1}} + \mathbf{\Psi t} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{11}$$

where $t$ is a time trend variable. We can decompose C and $\mathbf{\Psi}$ into

$$\mathbf{\Psi} = \boldsymbol{a}\mathbf{\Psi_1} + \boldsymbol{a_0}\mathbf{\Psi_2} \tag{12}$$

$$\boldsymbol{C} = \boldsymbol{aC_1} + \boldsymbol{a_0C_2} \tag{13}$$

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 (8) and (7) into Equation (6), we get

$$\Delta\mathbf{Y_t} = \boldsymbol{a}\begin{pmatrix}\boldsymbol{\beta}\\ \boldsymbol{C_1}\\ \mathbf{\Psi_1}\end{pmatrix}'\mathbf{Y_{t-1}} + \Phi_1\Delta\mathbf{Y_{t-1}} + \boldsymbol{a_0C_2} + \boldsymbol{a_0}\mathbf{\Psi_2 t} + \boldsymbol{\varepsilon}_\mathbf{t} \tag{14}$$

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).

**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 | $\mathbf{\Psi_2} \neq 0; \mathbf{\Psi_1} \neq \mathbf{0}; \boldsymbol{C_2} \neq \mathbf{0}; \boldsymbol{C_1} \neq \mathbf{0}$ |

Case 1 neither allows for any deterministic trend in the data nor for an intercept nor for a trend variable in the cointegration equations. This is an unusual specification, which is rarely used. In Case 2, the model does not have any linear trend in the data, but it allows for an intercept in the cointegration-space. This is the minimum deterministic component that is suggested by Hansen and Juselius (2002) and Johansen (2009), because intercepts can account for the difference in measurement units of included variables. In addition to allowing for intercepts in the cointegration space, Case 3 also allows for linear trends in the data. It is assumed that there are no trends in the cointegration-space, since the linear trends enter the VECM equation as drift (constant) terms. In case 4, intercepts and linear trends are present in the cointegration space, in addition to the drift terms. The linear trends in the cointegrated space ($\mathbf{\Psi_1}$) allow $r$ trend-stationary stochastic variables, meaning variables that are stationary after de-trending, and $n - r$ variables that are integrated of order one, I(1) process that has a linear trend. Therefore, this is the model to use in case variables are trend-stationary. Case 5 places no restrictions on any deterministic components. This case allows for linear trends in the differenced series, $\Delta Y_t$, and therefore quadratic trends in $Y_t$. Hansen and Juselius (2002) consider this case to be uncommon. They argue that this may be an outcome of a model mis-specification and suggest more variables to be used in order to increase the information content and to account for quadratic trends.

Since cases 1 and 5 are quite atypical, in this research only models 2-4 will be considered.

There are two approaches to determine the number of cointegration relationships, one of them is to plot the graph of the vector $Y_t$ in order to assess the deterministic component of the data and then to test the specific model for cointegration and the other one is to test the joint hypothesis of both rank order and the deterministic component (Johansen,1991). The last approach is performed using the Pantula principle (Pantula, 1989).

According to the Pantula Principle all three cases are estimated and the results are presented from the most restrictive ($Case\ 2\ and\ r = 0$) to the least restrictive ($Case\ 4\ and\ r = n - 1$). The idea behind this principle is to move from the most restrictive model to the least restrictive one and compare the trace test statistic to its critical value at each stage. The test is finalized when the null hypothesis is not rejected for the first time.

Even though the Pantula Principle is extremely useful at determining cointegration rank of several data series, one should be also aware of its shortcomings. There are several research papers that have analyzed the problem of deterministic specifications in this methodological procedure. Toda (1995) notes that despite the fact that the procedure generally correctly determines the cointegration rank, it systemically fails to detect the presence of linear trend in the data. That is, the procedure usually suggests specifying Model 2 even when the true process is Model 3. Doornik et al. (1998) analyzed the effect of an incorrect specification of deterministic components when investigating for contegration rank. The found evidence that non-including a restricted trend when it is present in the series generates distortions in test size, while including an unrestricted trend leads to a loss in test power. Franses (2001) provides some practical advice for the specification of deterministic components in the cointegration tests. He suggests that only two of the five possible modes are appealing in cointegration analysis: Model 2, which is useful when none of the series shows trend and Model 4 that should be used when some or all series show trend.

In order to be more accurate, we will try to analyze the results from the Pantula Principle by taking into account the presence of trend and/or intercept in the data series we examine.

### *3.5 Granger causality test*

Granger causality is different from simple causality. For example, causality from A to B indicates that *A* causes *B* directly. On the other hand, 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. A variable *X* Granger-causes *Y* if the past changes in *X* can project current values of *Y*. If *X* Granger-causes *Y*, this is called unidirectional causality. If *X* Granger-causes *Y* and *Y* also Granger-causes X then this is considered to be a bi-directional causality link (Brooks, 2002)

When we conduct a linear Granger causality test, we should account for two cases, depending 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 in matrix form is estimated:

$$\begin{pmatrix} \Delta \boldsymbol{Y_{1,t}} \\ \Delta \boldsymbol{Y_{2,t}} \\ \vdots \\ \Delta \boldsymbol{Y_{n,t}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{A_{10}} \\ \boldsymbol{A_{20}} \\ \vdots \\ \boldsymbol{A_{n0}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{A_{11}(L)} & \boldsymbol{A_{12}(L)} & \dots & \boldsymbol{A_{1n}(L)} \\ \boldsymbol{A_{21}(L)} & \boldsymbol{A_{22}(L)} & & \boldsymbol{A_{2n}(L)} \\ & \vdots & \ddots & \vdots \\ \boldsymbol{A_{n1}(L)} & \boldsymbol{A_{n2}(L)} & \cdots & \boldsymbol{A_{nn}(L)} \end{pmatrix} \begin{pmatrix} \Delta \boldsymbol{Y_{1,t-1}} \\ \Delta \boldsymbol{Y_{2,t-1}} \\ \vdots \\ \Delta \boldsymbol{Y_{n,t-1}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\varepsilon_{1,t}} \\ \boldsymbol{\varepsilon_{2,t}} \\ \vdots \\ \boldsymbol{\varepsilon_{n,t}} \end{pmatrix} \quad (15)$$

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 L$x_t$=$x_{t-1}$, $A_{i0}$ are intercept parameters, $A_{ij}(L)$ are polynomials in the lagged operator L, such that $A_{ij}(L) = a_{ij}(0)L^0 + a_{ij}(1)L^1 + \cdots + a_{ij}(p-1)L^{p-1}$. In practice it is common to set all the equations to have the same lag length $(p)$ for each variable; therefore, a similar $p$ will be chosen for all the lag polynomials of coefficients $A_{ij}(L)$. Since our lagged terms' coefficient matrix is of size $(nxn)$, we have to test $n(n-1)$ null hypotheses of (non-) Granger causality. For example, the null hypothesis that $Y_1$ is Granger-caused by $Y_2$ can be written as follows:

$$\mathbf{H_0}: a_{12}(d) = 0, \forall d \in \{0,1, \dots, p-1\}$$

$$\mathbf{H_1}: \exists d \in \{1,2,\dots,p\}, \text{such that } a_{12}(d) \neq 0$$

**ii)** If variables are cointegrated, and Error Correction Mechanism (ECM) must be added to equation 15, therefore, the following model will be tested:

$$\begin{pmatrix} \Delta Y_{1,t} \\ \Delta Y_{2,t} \\ \vdots \\ \Delta Y_{n,t} \end{pmatrix} = \begin{pmatrix} A_{10} \\ A_{20} \\ \vdots \\ A_{n0} \end{pmatrix} + \begin{pmatrix} A_{11}(L) & A_{12}(L) & \cdots & A_{1n}(L) \\ A_{21}(L) & A_{22}(L) & & A_{2n}(L) \\ & \vdots & \ddots & \vdots \\ A_{n1}(L) & A_{n2}(L) & \cdots & A_{nn}(L) \end{pmatrix} \begin{pmatrix} \Delta Y_{1,t-1} \\ \Delta Y_{2,t-1} \\ \vdots \\ \Delta Y_{n,t-1} \end{pmatrix} + \begin{pmatrix} \aleph_0 \\ \aleph_1 \\ \vdots \\ \aleph_n \end{pmatrix} (\varepsilon_{t-1}) + \begin{pmatrix} u_{1,t} \\ u_{2,t} \\ \vdots \\ u_{n,t} \end{pmatrix} \quad (16)$$

In this case we only introduce lagged error terms from the previously mentioned $VAR(p)$ model. In addition, due to this adjustment the null hypothesis is changed as well. Following the previous example, the null hypothesis that $Y_1$ is Granger-caused by $Y_2$ can be written as follows:

$$\mathbf{H_0}: a_{12}(d) \& \aleph_0 = 0, \forall d \in \{0,1,\dots,p-1\}$$

$$\mathbf{H_1}: \exists d \in \{1,2,\dots,p\}, a_{12}(d) \neq 0 \text{ or } \aleph_0 \neq 0$$

At this point, we are concerned with finding short-term relationship between stock markets of interest. If price series of the EU, U.S. and Russia's stock market indices are not cointegrated then we will use the equation 15 to estimate the Granger causality linkage, but if price series are cointegrated then we will use the VECM model portrayed above (equation 16). If price series are not cointegrated, then the matrix notation on the model on which Granger causality test will be conducted will as follows (assume for now that the lag length $(p)$ is 1):

$$\begin{pmatrix} r_t^{U.S} \\ r_t^{E.U} \\ r_t^{RU} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} + \begin{pmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) \end{pmatrix} \begin{pmatrix} r_{t-1}^{U.S} \\ r_{t-1}^{E.U} \\ r_{t-1}^{RU} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{pmatrix} \quad (17)$$

where $r_t^{U.S} = \ln\left(\frac{P_t^{U.S}}{P_{t-1}^{U.S}}\right)$, $r_t^{EU} \ln\left(\frac{P_t^{EU}}{P_{t-1}^{EU}}\right)$ and $r_t^{RU} \ln\left(\frac{P_t^{RU}}{P_{t-1}^{RU}}\right)$ are daily returns at the time $t$ of the U.S., EU and Russian equity markets, respectively; $P_t^{U.S}$, $P_t^{EU}$, $P_t^{RU}$ are stock market index values of the U.S., EU and Russia at time *t* and $A_{ij}$ is a polynomial of coefficients of lagged returns. In this case, since the lag length was assumed to be 1, we can write $A_{11}$(L)=$a_{11}$(0)*$L^0 *$ $r_{t-1}^{U.S}$=$a_{11}$(0)* $r_{t-1}^{U.S}$, which basically denotes the product between lagged U.S. return of order 1 and its coefficient.

It should be mentioned that Granger-causality test only denotes the correlation but not a direct causal relation between a current value of one variable and the previous values of another variable (Brooks, 2002). In addition, even though Granger-causality tests in VAR analyze whether the current value of a dependent variable can be explained by the past levels of an independent variable, they do not clarify the sign of the linkage among the analyzed variables and the duration of the causality linkages. Therefore, in order to conduct a more thorough analysis, further information will be provided by impulse response and variance decomposition analyses.

### *3.6 Generalized impulse response function*

An impulse response function presents the reaction of a dynamic system to external changes. In particular, VAR's impulse response function analyzes how the dependent variable reacts to shocks from each independent variable. The total effects of unit shocks are quantified by summing the coefficients of impulse response functions. 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.

Let us simplify the $VAR(p)$ model from equation 6 to an $1x1$ $AR(1)$ model. In addition, let us assume that the regression equation doesn't have an intercept and a deterministic trend. We can re-write the regression equation as follows:

$$\boldsymbol{y_t = \varphi y_{t-1} + \varepsilon_t} \tag{18}$$

Recursively substituting $n-1$ times the $y$ factors in the right-hand side of the equation we get

$$\boldsymbol{y_t = \varphi^n y_{t-n} + \varphi^{n-1}\varepsilon_{t-n+1} + \cdots + \varphi^2\varepsilon_{t-2} + \varphi^1\varepsilon_{t-1} + \varepsilon_t} \tag{19}$$

For a stable AR process ($|\varphi| < 1$), so $\lim_{n\to\infty} \varphi^n y_{t-n} = 0$ then

$$\boldsymbol{y_t = \sum_{i=0}^{\infty} \varphi^i \, \varepsilon_{t-i}} \tag{20}$$

Let us say $B_i$=$\varphi^i$ and use the vector representation for further analysis. We can write the tri-variate vector representation of the above MA(∞) process as $y_t = B(L)\varepsilon_t$, where $\varepsilon_t \equiv [\varepsilon_{1t} \quad \varepsilon_{2t} \quad \varepsilon_{3t}]'$ and $B(L) = B_0L^0 + B_1L^1 + \cdots$, where $\{B_0, B_1, \ldots\}$ define impulse response functions and $L$ is the backward operator. Precisely, $B(L)$ can be denoted as

$$\boldsymbol{B(L) = \begin{bmatrix} b_{11}(L) & b_{12}(L) & b_{13}(L) \\ b_{21}(L) & b_{22}(L) & b_{23}(L) \\ b_{31}(L) & b_{32}(L) & b_{33}(L) \end{bmatrix}} \tag{21}$$

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

$$\boldsymbol{B_h} = \frac{\partial \boldsymbol{y_{t+h}}}{\partial \boldsymbol{\varepsilon_t}'} = \begin{bmatrix} \frac{\partial \boldsymbol{y_{1,t+h}}}{\partial \boldsymbol{\varepsilon_{1,t}}} & \frac{\partial \boldsymbol{y_{1,t+h}}}{\partial \boldsymbol{\varepsilon_{2,t}}} & \frac{\partial \boldsymbol{y_{1,t+h}}}{\partial \boldsymbol{\varepsilon_{3,t}}} \\ \frac{\partial \boldsymbol{y_{2,t+h}}}{\partial \boldsymbol{\varepsilon_{1,t}}} & \frac{\partial \boldsymbol{y_{2,t+h}}}{\partial \boldsymbol{\varepsilon_{2,t}}} & \frac{\partial \boldsymbol{y_{2,t+h}}}{\partial \boldsymbol{\varepsilon_{3,t}}} \\ \frac{\partial \boldsymbol{y_{3,t+h}}}{\partial \boldsymbol{\varepsilon_{1,t}}} & \frac{\partial \boldsymbol{y_{3,t+h}}}{\partial \boldsymbol{\varepsilon_{2,t}}} & \frac{\partial \boldsymbol{y_{3,t+h}}}{\partial \boldsymbol{\varepsilon_{3,t}}} \end{bmatrix} \tag{22}$$

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:

$$\boldsymbol{\psi_{i,j}^{g}(h)} = \frac{\boldsymbol{B_h \Sigma e_j}}{\sqrt{\boldsymbol{\sigma_{jj}}}} \tag{23}$$

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 6) in the period $t$, $\sigma_{jj}$ 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 $\Sigma$ is $nxn$ variance-covariance matrix of the error term.

### *3.7 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). In addition, variance decomposition is also a powerful tool at predicting financial time series.

Let us start the description of the methodology for variance decomposition analysis with the moving average representation of a VAR and let us assume standard distributed error terms:

$$\boldsymbol{y_t = B(L)\varepsilon_t,\ E(\varepsilon_t \varepsilon_t') = I} \tag{24}$$

In a tri-variate model one step ahead forecast error variance can be represented as

$$\boldsymbol{y_{t+1} - \hat{y}_{t+1}} = \boldsymbol{B_0 \varepsilon_{t+1}} = \begin{pmatrix} \boldsymbol{b_{pp,0}} & \boldsymbol{b_{pq,0}} & \boldsymbol{b_{pr,0}} \\ \boldsymbol{b_{qp,0}} & \boldsymbol{b_{qq,0}} & \boldsymbol{b_{qr,0}} \\ \boldsymbol{b_{rp,0}} & \boldsymbol{b_{rq,0}} & \boldsymbol{b_{rr,0}} \end{pmatrix} \begin{pmatrix} \boldsymbol{\varepsilon_{p,t+1}} \\ \boldsymbol{\varepsilon_{q,t+1}} \\ \boldsymbol{\varepsilon_{r,t+1}} \end{pmatrix} \tag{25}$$

where $B(L) = B_0 L^0 + B_1 L^1 + \cdots$. Because $\varepsilon$ are assumed to be uncorrelated and have unit variance then we can express the variance as follows:

$$\boldsymbol{var_t(p_{t+1}) = b^2_{pp,0}\sigma^2_{pp}(\varepsilon_p) + b^2_{qq,0}\sigma^2_{qq}(\varepsilon_q) + b^2_{rr,0}\sigma^2_{rr}(\varepsilon_r) = b^2_{pp,0} + b^2_{qq,0} + b^2_{rr,0}} \tag{26}$$

Equation 26 can be similarly written for $q$ and $r$. Therefore, $b^2_{pp,0}$ gives the amount of one-step forecast error variance of $p$ due to $\varepsilon_p$ shock, $b^2_{qq,0}$ provides the amount of one-step forecast variance of $p$ due to $q$ and $b^2_{rr,0}$- one step forecast variance due to $r$. Our results can be written more formally as

$$\boldsymbol{var_t(y_{t+1}) = B_0 B'_0} \tag{27}$$

Let us define

$$\boldsymbol{I_1} = \begin{pmatrix} \mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix} \boldsymbol{I_2} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix} \boldsymbol{I_3} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} \end{pmatrix} \tag{28}$$

The part of one step ahead forecast variance due to the first $(p)$ shock can be written as $B_0 I_1 B'_0$, the part due to the second $(q)$ shock is $B_0 I_2 B'_0$ etc. All these parts will add up to

$$\boldsymbol{B_0 B'_0 = B_0 I_1 B'_0 + B_0 I_2 B'_0 + \cdots} \tag{29}$$

$I_\tau$ can be thought of as a new covariance matrix in which all shocks but the $\tau' th$ are turned off, then the total variance of the forecast errors must be equal to the part due to the $\tau' th$ shock, and it is obviously equal to $B_0 I_\tau B'_0$.

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

$$\boldsymbol{y_{t+k} - \hat{y}_{t+k} = B_0 \varepsilon_{t+k} + B_1 \varepsilon_{t+k-1} + \cdots + B_{k-1} \varepsilon_{t+1}} \tag{30}$$

and

$$\boldsymbol{var_t(y_{t+k}) = B_0 B'_0 + B_1 B'_1 + \cdots + B_{k-1} B'_{k-1}} \tag{31}$$

then

$$\boldsymbol{\vartheta_{k,\tau} = \sum_{j=0}^{k-1} B_j I_\tau B'_j} \tag{32}$$

is the variance of k step ahead cumulative forecast errors due to the $\tau' th$ shock, and the total variance of forecast error at the time $t + k$ is

$$\boldsymbol{var_t(y_{t+k}) = \sum_\tau \vartheta_{k,\tau}} \tag{33}$$

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

$$\boldsymbol{\vartheta_\tau} = \sum_{j=0}^{\infty} \boldsymbol{B_j I_\tau B_j'} \tag{34}$$

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

$$\boldsymbol{var_t(y_{t+k})} = \sum\nolimits_{\tau} \boldsymbol{\vartheta_\tau} \tag{35}$$

## *3.8 Multivariate GARCH*

### 3.8.1 Multivariate GARCH model

Usually, in econometric models, error terms are considered to be homoscedastic (constant) over time; however, this assumption is less likely to hold for financial time series, since they are quite volatile. Some financial time series have "long-memory" (observations that are separated by a large time-span show statistically significant correlation). Another peculiarity of financial time series is "volatility clustering", when periods of high (low) volatility are followed by periods of high (low) volatility (Brooks, 2002).

Engle (1982) developed the Autoregressive Conditional Heteroskedasticity (ARCH) model that allows the conditional variance to vary across time. Bollerslev (1986) extended the $ARCH(q)$ model to a more general one- $GARCH(p, q)$ (Generalized Autoregressive Conditional Heteroskedasticity) model, which allows the conditional variance to depend on its precedent lags. Here and thereafter, $q$ denotes the length of ARCH lags (past innovation elements), while $p$ denotes the length of GARCH lags (past volatility elements).

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 the following equation:

$$\mathbf{R_t} = \boldsymbol{\alpha_0} + \mathbf{\Gamma R_{t-1}} + \boldsymbol{\varepsilon_t} \tag{36}$$

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

$$\boldsymbol{\varepsilon_t} = \mathbf{H_t^{1/2}(\boldsymbol{\theta})Z_t} \tag{37}$$

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($Z_t$)=$I_N$. $\mathbf{H}_t$ 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:

$$\boldsymbol{H_t} = \begin{pmatrix} \boldsymbol{h_{11,t}} & \boldsymbol{h_{12,t}} & \boldsymbol{h_{13,t}} \\ \boldsymbol{h_{21,t}} & \boldsymbol{h_{22,t}} & \boldsymbol{h_{23,t}} \\ \boldsymbol{h_{31,t}} & \boldsymbol{h_{32,t}} & \boldsymbol{h_{33,t}} \end{pmatrix} \tag{38}$$

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, $\varepsilon_t$, and lagged conditional variance-covariance matrix, $H_t$ (Engle & Kroner, 1995). One particular feature of this specification is that it is sufficiently general, allowing the conditional variance and covariance of stock markets to influence each other, and at the same time, it does not require the estimation of a large number of parameters (Karolyi, 1995). The model ensures that the variance-covariance matrix is positive semi-definite in the optimization process, thus, fulfilling the required condition that estimated variances should be zero or positive. The BEKK parameterization of GARCH can be written as follows:

$$\boldsymbol{H_t = B'B + C'\varepsilon'_{t-1}\varepsilon_{t-1}C + G'H_{t-1}G} \tag{39}$$

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 $GARCH(1,1)$ 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). In our case with three countries $(N = 3)$ and $p = q = 1$, the above equation becomes a trivariate GARCH(1,1) which can be outlined as follows:

$$\begin{pmatrix} \boldsymbol{h_{11,t}} & \boldsymbol{h_{12,t}} & \boldsymbol{h_{13,t}} \\ \boldsymbol{h_{21,t}} & \boldsymbol{h_{22,t}} & \boldsymbol{h_{23,t}} \\ \boldsymbol{h_{31,t}} & \boldsymbol{h_{32,t}} & \boldsymbol{h_{33,t}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{b_{11}} & \boldsymbol{b_{12}} & \boldsymbol{b_{13}} \\ \mathbf{0} & \boldsymbol{b_{22}} & \boldsymbol{b_{23}} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{b_{33}} \end{pmatrix}' \begin{pmatrix} \boldsymbol{b_{11}} & \mathbf{0} & \mathbf{0} \\ \boldsymbol{b_{21}} & \boldsymbol{b_{22}} & \mathbf{0} \\ \boldsymbol{b_{31}} & \boldsymbol{b_{32}} & \boldsymbol{b_{33}} \end{pmatrix} +$$
$$+ \begin{pmatrix} \boldsymbol{c_{11}} & \boldsymbol{c_{12}} & \boldsymbol{c_{13}} \\ \boldsymbol{c_{21}} & \boldsymbol{c_{22}} & \boldsymbol{c_{23}} \\ \boldsymbol{c_{32}} & \boldsymbol{c_{32}} & \boldsymbol{c_{33}} \end{pmatrix}' \begin{pmatrix} \boldsymbol{\varepsilon^2_{1,t-1}} & \boldsymbol{\varepsilon_{1,t-1;2,t-1}} & \boldsymbol{\varepsilon_{1,t-1;3,t-1}} \\ \boldsymbol{\varepsilon_{2,t-1;1,t-1}} & \boldsymbol{\varepsilon^2_{2,t-1}} & \boldsymbol{\varepsilon_{2,t-1;3,t-1}} \\ \boldsymbol{\varepsilon_{3,t-1;1,t-1}} & \boldsymbol{\varepsilon_{3,t-1;2,t-1}} & \boldsymbol{\varepsilon^2_{3,t-1}} \end{pmatrix} \begin{pmatrix} \boldsymbol{c_{11}} & \boldsymbol{c_{12}} & \boldsymbol{c_{13}} \\ \boldsymbol{c_{21}} & \boldsymbol{c_{22}} & \boldsymbol{c_{23}} \\ \boldsymbol{c_{32}} & \boldsymbol{c_{32}} & \boldsymbol{c_{33}} \end{pmatrix} + \tag{40}$$

$$+\begin{pmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{32} & g_{32} & g_{33} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t-1} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t-1} & h_{33,t-1} \end{pmatrix} \begin{pmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{32} & g_{32} & g_{33} \end{pmatrix}$$

The symmetric matrix $C$ captures the ARCH effects, the element $c_{ij}$ measure the degree of innovation from market $i$ to market $j$. On the other hand matrix $G$ focuses on the GARCH effects, the element $g_{ij}$ in matrix $G$ denotes the persistence of conditional volatility between market $i$ and market $j$. In other words, the diagonal parameters of $C$ and $G - c_{11}$, $c_{22}$, $c_{33}$ and $g_{11}$, $g_{22}$, $g_{33}$ $-$capture the effect of own past shocks and volatility on a series' current volatility levels. The off-diagonal parameters in matrices $C$ and $G$, $c_{ij}$ and $g_{ij}$, measure the cross-market influence of shock  and volatility spillover effects, respectively.

In order to estimate the parameters of the multivariate GARCH model, the following log likelihood function should be maximized:

$$L(\theta) = -\frac{TN}{2} log2\pi - \frac{1}{2}\sum_{i=1}^{T}(\log|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t) \tag{41}$$

Where $\theta$ denotes the parameters to be estimated, N is the number of time series in the system and T is the number of observations. The log likelihood is maximized by the BHHH (Berndt, Hall, Hall & Hausman, 1978) algorithm.

# 4 DATA

## *4.1 Choice of stock indices*

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

- The Russian Trading System Index (*RTS*) is a cap-weighted composite index based on the prices of the 50 most liquid Russian stocks of the largest and dynamically developing Russian issuers present at the Moscow Exchange. The *RTS* Index was launched on 1 September 1995 at a base value of 100. The Index is calculated in real time by the Moscow Exchange in U.S. dollars and disseminated by the *S&P Dow Jones* indices (Bloomberg, 2015a). We selected the *RTS* as a proxy for the Russian market portfolio, instead of the *MICEX* index because the *RTS* is calculated in U.S. dollars and it better depicts the negative impact of the Western sanctions on the Russian economy (Abramov, 2014). Trenca, Petria & Dezsi (2013) suggest aggravating trade linkages as the channel for financial contagion. Given that the sanctions imposed on Russia influenced the trade among these word players (Council Implementing Regulation, 2014b; Rapoza, 2014) and considering that the *RTS* better captures the impact of these sanctions on Russia's stock market and economy in general, as it takes into account the effect of the falling ruble, we consider that the *RTS* better proxies the contagion transmission from the Russian stock market to the stock markets of the EU and the U.S.
- The *S&P 500* is considered as the best single gauge of large cap U.S. equities. The index is comprised of 500 leading companies and it covers about 80% of the available market capitalization of the U.S. (S&P Dow Jones Indices, 2015).
- The *STOXX Europe 50* Index, Europe's leading Blue-chip index, offers a representation of supersector leaders in Europe. The index covers 50 stocks from 18 European countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK (STOXX, 2015). We would like to point out that this is the best proxy for the EU equity market that we have found, since almost all of the countries mentioned above are EU members. Two of them, namely Norway and Switzerland, are not members of the EU, but they are members of European Free Trade Agreement (EFTA), which makes them partly committed to the EU's economy and regulations (European Free Trade Association, n.d.). Switzerland not only accepted the EU's blacklist of Russian citizens,

but also further expanded its sanctions against Russia (MacLucas, 2014). In addition, the Swiss government imposed a requirement for five major Russian banks to ask for authorization in order to issue long-term financial instruments in Switzerland (Federal Chancellery of Switzerland, 2014). On the other side, Norway adopted even more severe sanctions against Russia than the ones imposed by the U.S. and EU. Russian state-owned banks are forbidden from taking long-term and mid-term loans in this country. Technology aid for the Russian oil sector is prohibited as well (Mohsin, 2014). As a response, Russia imposed a total ban on food imports from Norway (Government of Russian Federation, 2014).

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 by multiplying its daily closing price values with the respective daily USD/EUR exchange rate. Transforming the prices of all indices into a common currency is a usual practice for papers analyzing dynamic linkages among stock markets (Valadkhani and Chancharat, 2008; Moroza, 2008; Khan, 2011; Tripti, 2015).

### *4.2 Data Collection*

The daily historical closing prices of *STOXX Europe 50*, *S&P 500* and *RTS* equity indices were gathered from the *Thomson Reuters Datastream*. The USD/EUR exchange rate was retrieved from the same source.

We used daily data because the higher number of observations the better we can capture the spillover effects that are temporary and short-lasting (Maghyereh and Awartani, 2012). Taking into account that Russia's 2014-2015 crisis started just a year ago (a specific date can be found in the results of the structural break analysis) and that we need more frequent data in order to provide more efficient estimators for the GARCH-BEKK model (Worthington & Higgs, 2004), it is more reasonable for us to use daily data.

In addition, to perform structural break tests, we retrieved the *RTS Volatility* Index from the *Thomson Reuters Datastream*.

We chose to retrieve the required information from *Thomson Reuters Datstream* because this database provides easy access to the data. Moreover, Thomson Reuters validates the data by cross-checking the information that is submitted by stock exchanges with several different public sources. This and several other quality control procedures ensure data credibility (Thomson

Reuters, 2008). In addition, the gathered data is already adjusted for the different holidays in Russia, the EU and U.S., meaning that no adjustments to the raw data are needed.

### *4.3 Description of the data*

The data of *RTS Volatility* Index contains of 2,386 daily observations and it is available for the period from 10 January 2006 until 3 March 2015.

We collected price data of daily stock indices from 1 September 1995 until 3 March 2015 for all the stock indices (*S&P 500*, *STOXX Europe 50* and *RTS*). Therefore we have a total of 5,088 observations per each equity index. The data was retrieved starting from 1 September 1995 because this is the date when the *RTS* index was introduced. On the other hand, 3 March is the last day in all of our data series because of the time constraints imposed on writing this thesis.

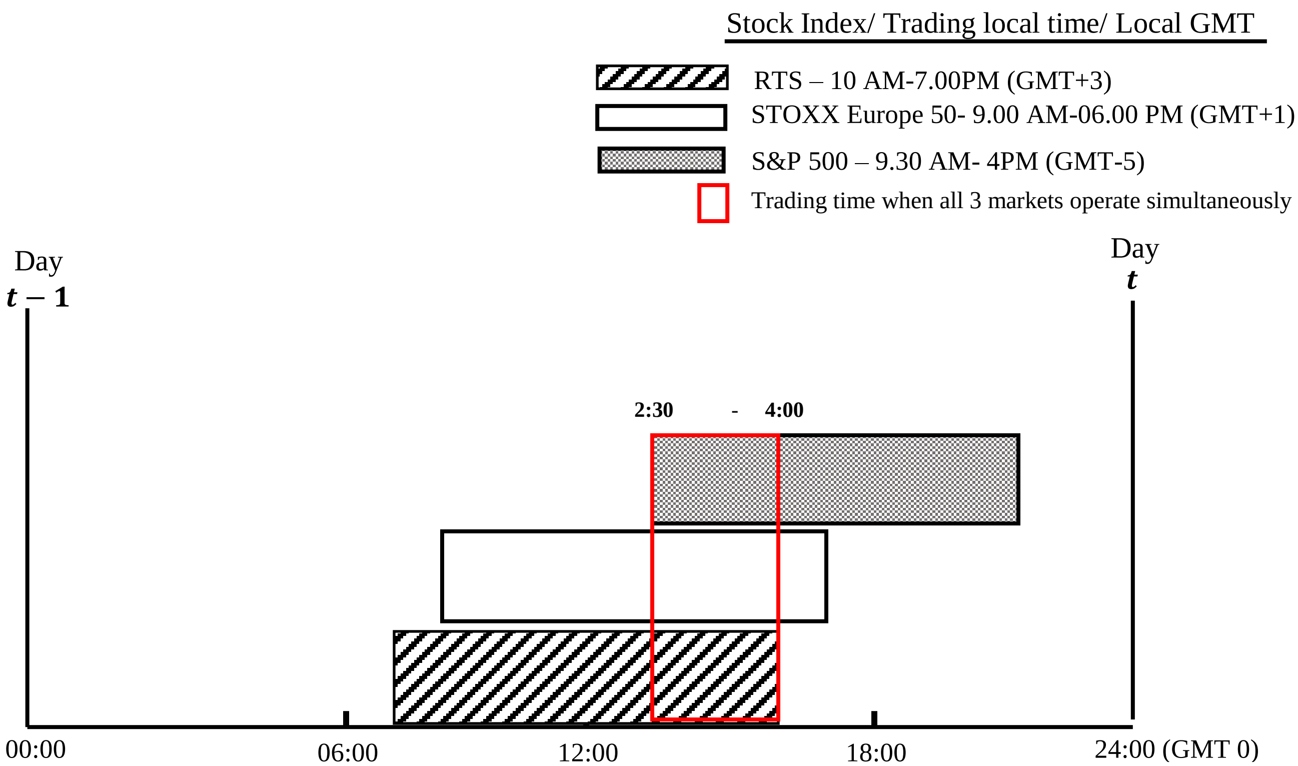
Our analyzed sub-sample periods will depend on the results of the Bai-Perron structural break analysis, which is run on the *RTS* volatility index. Using this test, we will identify two sub-samples periods. One sub-sample period will represent a stable period and the other one will represent the period of Russia's 2014–2015 crisis.

### *4.4 Time zones and non-synchronization*

Time zones are particularly important when analyzing different international markets using daily data. The non-synchronism problem arises when each market operates in different time zones with different opening and closing times. The opening and closing times of stock exchanges are depicted in Graph 1. Note that, as the *STOXX Europe 50* equity index aggregates 18 of Europe's stock markets, the price changes start to be recorded when the first of the European markets open and end when the last of the markets closes (STOXX, 2015). Thus, the Eurozone's market is open nine hours per day.

To avoid the non-synchronization of prices, Sheppard (2013) suggests taking prices at a time when all stock exchanges are jointly open. These prices are called pseudo-prices and by using this method it would allow us to capture the contemporaneous co-variation between our three assets. All three indices are simultaneously open for one and a half trading hours in the same calendar day; however, the *Thomson Reuters Datastream* does not provide us with hourly price data. Moroza (2008) suggests that even a one-and-a-half-hour overlap between the trading time of assets located in different countries is sufficient to capture the contemporaneous co-variation between asset prices and returns, thus the usage of contemporaneous daily closing prices is justified. In addition, different holidays in different countries may cause the non-synchronization of prices. To correct for this issue, Hoesli and Reka (2011) suggest using the previous trading day's closing price for the given holidays. As the *Thomson Reuters Datastream* adjusts the data, no adjustments are needed to the data set.

**Graph 1.** Trading hours in three stock markets, made by the authors



## 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, provided by the *Thomson Reuters Datastream*, 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. The data ranges from the inception of the *RTS* Volatility Index on 10 January 2006 until 3 March 2015. This particular index is calculated based on the Black-Merton-Sholes option pricing formula (Loh, Martellini & Stoyanov, 2013). It shows the implied volatility or the market's expectations of volatility in the next month.

Both unit root tests (ADF and KPSS) suggest that the *RTS Volatility* Index series is stationary at a 5% significance level (see Appendix A). Therefore, we can proceed further with the Bai-Perron analysis. According to our test results, the volatility series exhibits five break-dates or six periods where the average volatility of the *RTS Volatility* Index differs substantially from the volatility in the previous period (see Graph 2 and Table 2). In addition, the robustness tests suggest that the number of actual breaks does not increase if the number of possible breaks specified in the Bai-Perron structural break test is extended beyond five.

**Graph 2** Structural breaks in the *RTS* implied volatility series, made by the authors using data from *Thomson Reuters Datastream*

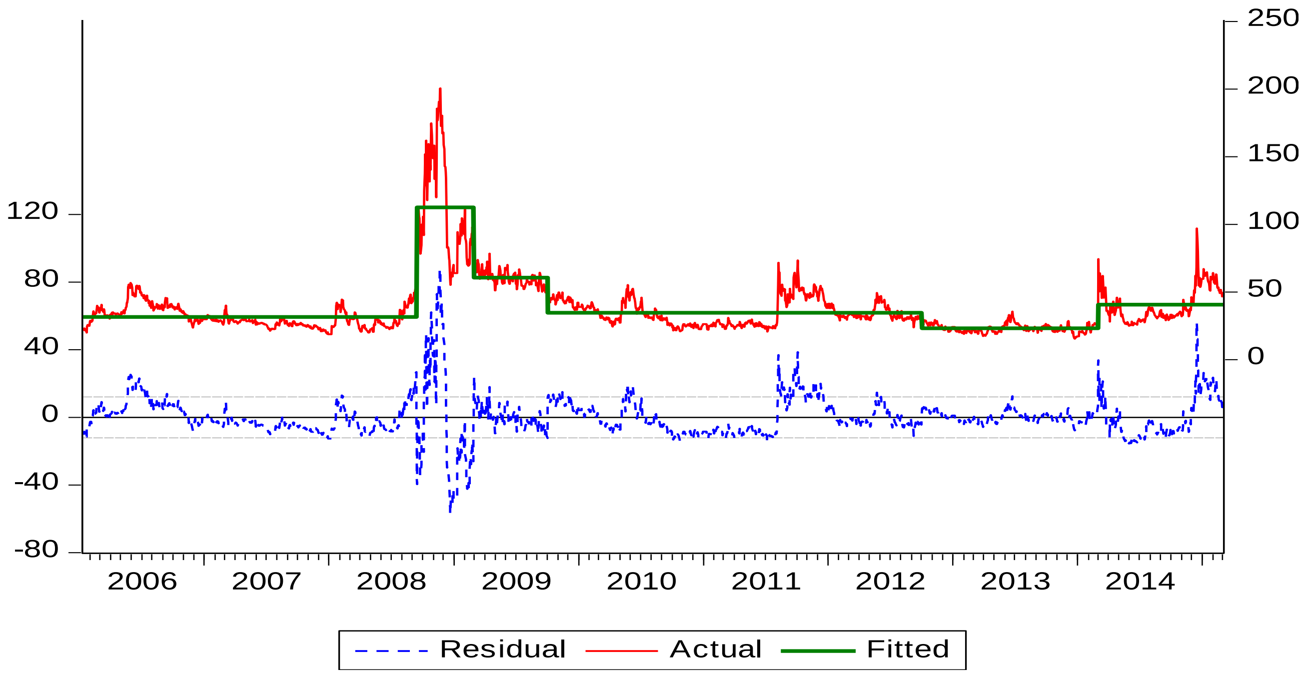


**Table 2** Regression output for structural break tests, made by the authors using data from *Thomson Reuters Datastream*

| 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.

According to our test results (see Table 2), the Russian equity market experienced a tranquil period in early 2006 and the period persisted for roughly two and a half years. Volatility during this period exhibited relatively low levels. Mala and Reddy (2007) suggest that the low volatility of Russia's equity market may have partially been caused by no changes in the Bank of Russia's refinancing rate, which was held fixed at 6.5%. Another possible explanation, given by Peiris and Dayarante (2012), is that the low volatility of exchange rate fluctuations caused low variations in equity prices. In fact, volatility of the EUR/RUB exchange rate was 4.345% during the first tranquil period, which is 163% lower than the average exchange rate volatility from 1995 till 2006. Further, the first break in the volatility occurred in mid-September 2008. Chenguel (2014) argues that the sub-prime crisis in the U.S. caused the increase in volatility in Russia's equity markets during that period. There was a subsequent break in the volatility half a year later, on 27 February 2009. The average level of volatility decreased as the majority of the information from the sub-prime crisis had already been spilled and the increasing price of gas diminished the uncertainty about stock market performance (Kramer, 2009). The third break in volatility was detected in early February 2009. At this point, equity market fluctuations decreased, returned to their pre-crisis level and persisted at this level for three years. The third successive drop in volatility occurred in early February 2012. This period exhibits the lowest average implied volatility in the *RTS Volatility* Index. However, the mild equity price fluctuations were distorted on 3 March 2014. This break occurred during the following trading day after the Russian Foreign Ministry officially admitted that Russian forces had seized Crimea (Ensor & Merat, 2014; Hufbauer, Cimino & Moran, 2014). Thus, the tranquil period of our study will range from 2 October 2012 till 28 February 2014, and the crisis period starts on 3 March 2014 and ends on 3 March 2015. This gives us 369 observations before the crisis and 262 observations during the crisis.

Furthermore, we conducted a robustness check of the break-dates by substituting the implied volatility data with the historical volatility of the *RTS* Index using the same time span as for the implied volatility data. In particular, we calculated the daily annualized volatility of the *RTS* index and after performing the Bai-Perron structural break test we found four breaks in the volatility series (see Appendix B, C). The periods of stability and crisis do not diverge by much from the periods determined using the *RTS* Volatility index. The tranquil period was found to persist from 10 September 2012 till 27 February 2014, and the crisis period lasts from 28 February 2014 till 3 March 2015.

### *5.2 Descriptive Statistics*

#### 5.2. 1 Pre-Crisis Period

Table 3 provides descriptive statistics of the returns of *S&P 500*, *STOXX Europe 50* and *RTS* stock indices before the Russian crisis. Note that the respective p-value is presented under the coefficient in parenthesis. The following formula was used to obtain the returns of an index:

$$R_{i,t} = ln\left(P_{i,t}\right) - \ln\,(P_{i,t-1}) \qquad (42)$$

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 $t-1$.

The highest average daily return during the tranquil period is observed in the U.S. equity market (0.068%) which is followed by *STOXX Europe 50* (0.006%) and the *RTS* equity index (-0.0048%). On the other hand, the highest daily volatility (measured using standard deviation) is recorded in the Russian equity markets (1.15%), followed by *STOXX Europe 50* (0.909%) and *S&P 500* (0.714%). As for the distribution properties of returns, the log-returns of all three stock indices, linked to their respective frequencies, resemble normal distribution. However, two distinct features must be noted: skewness and kurtosis. The skewness of the returns series is negative for all three indices. Therefore, it is more probable to receive abnormal negative returns rather than abnormal positive returns. In addition, the kurtosis exceeds the normal level of three, predicted by the Gaussian distribution, which means that there are more observations that lie around the mean returns, compared to the normal distribution. In fact, between one standard deviation lays 75.27%, 74.18% and 74.46% of the data of *S&P 500, STOXX Europe 50* and *RTS* index respectively. Seeing these two non-normalities in our empirical return distributions, we are not surprised that none of the three stock indices return series exhibits normality, according to the Jarque-Bera test statistic. Overall, all three return distributions are peaked and have heavy left tails. Furthermore, the Ljung-Box Q-test, Q(5), shows that none of the return series exhibits autocorrelation. Using squared return series, the Ljung-Box Q-test, $Q^2$ (5), shows that return series do not have heteroskedasticity or clustered errors, except for the *S&P 500*. In addition, the stable period returns do not show any ARCH effect.

**Table 3** Descriptive statistics of daily returns during tranquil/stable period, made by the authors using data from *Thomson Reuters Datastream*

| Stock index | Mean % | Standard deviation | Skewness | Kurtosis | Jarque-Bera Statistics | $\boldsymbol{Q(5)}$ | $\boldsymbol{Q^2(5)}$ | ARCH LM Statistics (Lag=5) |
|---|---|---|---|---|---|---|---|---|
| *S&P 500* | 0.00068 | 0.00714 | -0.43051 | 4.41427 | 42.15082*** (0.000) | 0.857 (0.973) | 12.737** (0.026) | 1.618492 (0.1542) |
| STOXX Europe 50 | 0.00060 | 0.00909 | -0.515032 | 5.242758 | 93.6491*** (0.000) | 5.787 (0.328) | 3.886 (0.566) | 1.439161 (0.2094) |
| *RTS* | -0.00048 | 0.01150 | -0.083990 | 4.27042 | 25.24856*** (0.000) | 3.037 (0.694) | 4.190 (0.522) | 1.149516 (0.334) |

*, ** and *** indicate significance of results at 10%, 5% and 1% significance level, respectively. The table reports the descriptive statistics of the stock index returns for *S&P 500*, *STOXX Europe 50* and *RTS* indices during the period from 2 October 2012 to 28 February 2014. The sample size is 369. $Q(5)$ and $Q^2(5)$ report the Ljung-Box portmaneu statistics with 5 lags for the return and square return series, respectively. ARCH LM test critical values were computed using F-statistic. $\mathrm{Jarque-Bera} = \frac{\mathrm{T}}{6}(\mathrm{Skew}^2 + \frac{1}{4}(\mathrm{Kurt}-3)^2 \sim \chi^2$. Where T represents the size of the sample, Skew shows the skewness level, and Kurt shows the kurtosis level in the data. $Q(p) = T(T+2)\sum_{i=1}^{p}\frac{\rho^2(i)}{T-i} \sim \chi^2$, where $\rho(i)$ shows the autocorrelation of the i[th] lag.

### 5.2.2 Crisis Period

Table 4 provides descriptive statistics of log returns during the Russian crisis. Similarly to the stable period, the *S&P 500* exhibits the highest average return rate (0.048%) of all three indices, followed by *STOXX Europe 50* (-0.033%) and *RTS* (-0.124%). If both states are compared, you can conclude that the mean return of all indices decreased. In the crisis period, the average volatility did not increase for the *S&P 500*, while mildly increasing (2%) for the *STOXX Europe 50*. However, the average volatility of the *RTS* increased by 126% compared to the tranquil period. Similarly to the pre-crisis period, the skewness is negative for all three indices. Thus, all series are more susceptible to negative shocks and exhibit heavy left tails. Furthermore, the levels of kurtosis of *S&P 500* and *STOXX Europe 50* have decreased, whereas the increase in kurtosis of the *RTS* index was 137%, thus exhibiting an aggressive evolution of distinct leptokurtic return distribution. The proportion of returns that lie between one standard deviation is 72.8%, 80.15% and 79.39% for *S&P 500, STOXX Europe 500* and *RTS,* respectively. Although one might assume that the stability of *STOXX Europe* and *RTS* increased, we must note that the standard deviation of returns increased, thus the risk increased. In addition, we reject the null hypothesis of the Jarque-Bera statistic of normality at 1% significance level for all return series. The Ljung-Box Q-test, Q(5), shows that *S&P 500* does not exhibit autocorrelation in the returns series, whereas the other two indices have autocorrelation between their returns. In comparison with the pre-crisis period, we reject the null hypothesis of Ljung-Box $Q^2$, $Q^2(5)$, that error terms are homeskedastic for all return series, thus the error terms exhibit clustering behaviour. In addition, the ARCH effect is present in all indices at 1% significance level.

**Table 4** Descriptive statistics of daily returns during the crisis period, made by the authors using data from *Thomson Reuters Datastream*

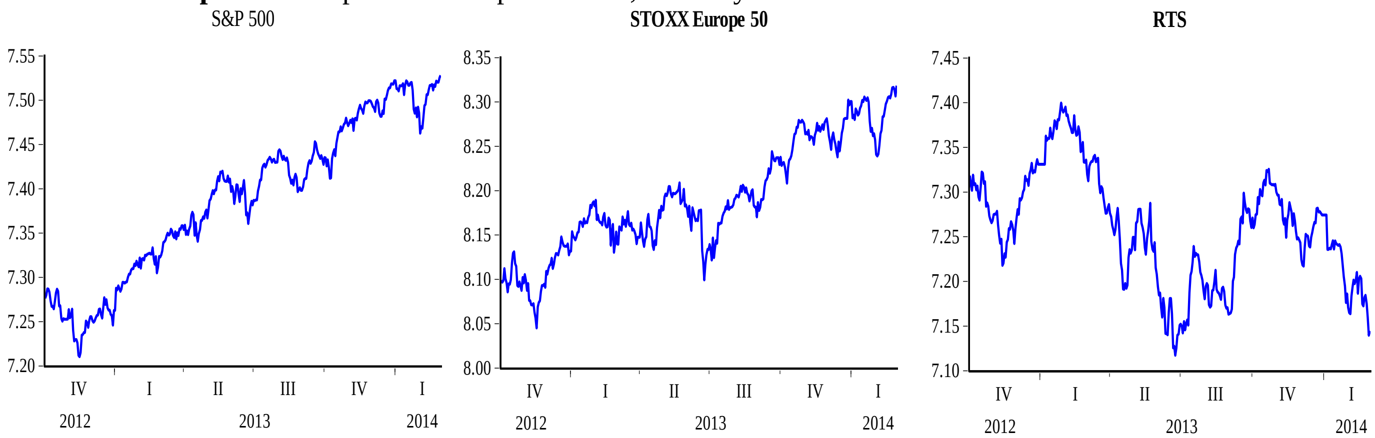
| Stock index | Mean | Standard Deviation | Skewness | Kurtosis | Jarque-Bera Statistics | $\boldsymbol{Q(5)}$ | $\boldsymbol{Q^2(5)}$ | ARCH LM Statistics (Lag=5) |
|---|---|---|---|---|---|---|---|---|
| *S&P 500* | 0.00048 | 0.00717 | -0.20125 | 3.9584 | 11.79527***<br>(0.002) | 1.8142<br>(0.874) | 48.052***<br>(0.000) | 48.0523***<br>(0.000) |
| STOXX Europe 50 | -0.00033 | 0.00928 | -0.20866 | 4.8466 | 39.12733***<br>(0.000) | 11.285**<br>(0.046) | 27.926***<br>(0.000) | 3.7002***<br>(0.003) |
| *RTS* | -0.00124 | 0.026026 | -0.24976 | 10.1243 | 556.8026***<br>(0.000) | 94.168***<br>(0.000) | 73.076***<br>(0.000) | 21.43602**<br>(0.000) |

*, ** and *** indicate significance of results at 10%, 5% and 1% significance level, respectively. The table reports the descriptive statistics of the stock index returns of *S&P 500*, *STOXX Europe 50* and *RTS* indices during the period from 3 March 2014 to 3 March 2015. The sample size is 262. $Q(5)$ and $Q^2(5)$ report the Ljung-Box portmaneu statistics with 5 lags for the return and square return series, respectively. ARCH LM test critical values were computed using F-statistic. $\text{Jarque} - \text{Bera} = \frac{\text{T}}{6}(\text{Skew}^2 + \frac{1}{4}(\text{Kurt} - 3)^2 \sim \chi^2$.Where T represents the size of the sample, Skew shows the skewness level, and Kurt shows the kurtosis level in the data. $Q(p) = T(T+2)\sum_{i=1}^{p}\frac{\rho^2(i)}{T-i} \sim \chi^2$, where ρ(i) shows the autocorrelation of the i$^{th}$ lag.

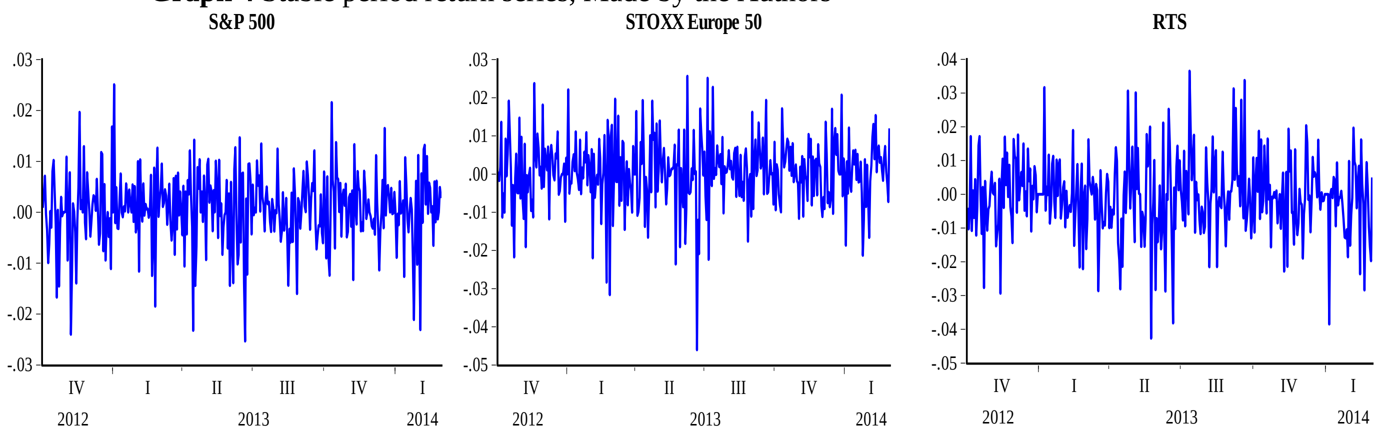
### *5.3. Unit root and stationary*

Before investigating the linkages among different stock markets, the Augmented Dickey-Fuller (ADF) and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests are employed to examine the stationarity properties of the level and return series. The null hypothesis of the ADF and the PP tests states that series have a unit root, while the null hypothesis of the KPSS tests is that the series are stationary. We perform the KPSS test to confirm the results of the ADF. If the two approaches provide contradictory results for regression equations with similar specifications of trend and drift terms, then the results of the KPSS test will be preferred. To confirm the presence of a trend and/or drift term in the regression equations, we will analyze the graphs of the index level series (prices) and that of the first difference in level series (returns), respectively (see Graphs 3, 4, 5, and 6).

**Graph 3** Stable period index price series, Made by the Authors

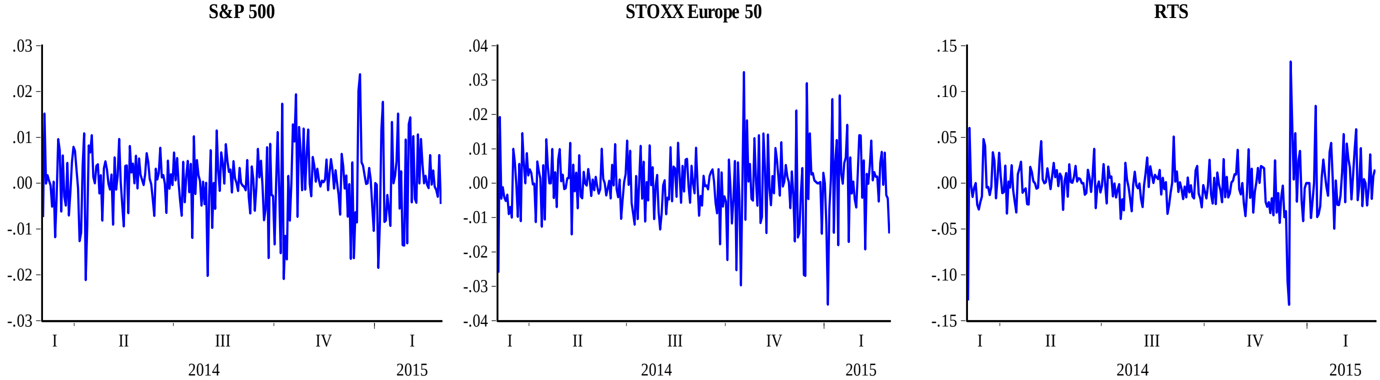



**Graph 4** Stable period return series, Made by the Authors




**Graph 5** Crisis period index price series, Made by the Authors

**Graph 6** Crisis period index return series, Made by the Authors




### 5.3.1 Stable Period

During the stable period, all log price (level) series do not start from the origin of the coordinate system. Moreover, two series (*S&P 500* and *STOXX Europe 50*) exhibit a clear upward trend. Thus we will use t-statistic and p-values of unit root tests with drift and/or deterministic trend. On the other hand, returns do not display a clear trending pattern; therefore, we will consider t-statistic and p-values for unit roots tests with neither an intercept nor a trend.

Graph 3 depicts all three stock index price series during the stable period. It can be easily seen that both *S&P 500* and *STOXX Europe 50* have an intercept and a trend; therefore, a unit root test with these specifications (equation 4) is more suitable. On the other hand, the *RTS* index has an intercept but it does not have an apparent trend, so a unit root test with and without a trend term will be performed (equations 3, 4).

The ADF test for both *S&P 500* and *STOXX Europe 50* level series rejects the null hypothesis of the presence of a unit root at a 5% significance level. On the other hand, the KPSS test rejects the null-hypothesis of the stationarity of the above-mentioned data series at 5% and 1% confidence levels respectively. Taking into account the higher power of the KPSS test to discern between a unit root and a near unit root processes (Kwiatkowski et al., 1992), the results from the KPSS test are preferred. For *RTS* stock index, the results from both ADF and KPSS tests coincide, thus the *RTS* index price series is non-stationary. It is important to mention that the KPSS test rejects the null hypothesis of the stationarity of this series irrespective of the presence of an intercept at 1% significance level (see Appendix D).

Graph 4 depicts the return series for all 3 stock indices. It can be seen that none of the return series has a trend. It is not obvious which series have an intercept so we will perform unit root tests on regression equations with and without an intercept (equations 2, 3). Taking into account that the KPSS test does not provide Lagrange Multiplier-statistic for regression equation with no trend, we will prefer the results provided by the ADF test.

According to the ADF test, we can reject the null-hypothesis of non-stationarity of time series at a 1% significance level for all return series, which means that all return series are stationary (see Appendix E).

**5.3.2 Crisis period**

Similarly to the stable period, all log price series have an intercept during the crisis period. In addition, *S&P 500* index series exhibit an upward trend. Therefore, we will rely on t-statistics and p-values of unit root tests with drift and/or deterministic trend.

Graph 5 outlines that *S&P 500* has an intercept and a trend, which suggests that we will use equation 4 to test for its stationarity. The *RTS* index and *STOXX Europe 50* do not have an apparent trend; therefore, we perform unit root tests with and without a trend term (equations 3,4).

The ADF test suggests that we cannot reject the null-hypothesis of non-stationarity in levels (prices) of all three stock index series. These results are reinforced by the KPSS test results, which suggest that we reject the null hypothesis of the stationarity of all three series at a 1% significance level. The results do not differ if we incorporate an intercept and a trend variable or just a trend variable (see Appendix F).

Graph 6 depicts the return series for all three stock indices. Similarly to the returns from the stable period, none of the return series from the crisis period has a trend. Again, since it is not clear which return series have an intercept, we will conduct unit root tests on regression equations with and without an intercept (equations 2, 3). Again, we will prefer the results of the ADF test, rather than the ones provided by KPSS, since the latter one does not provide t-statistic and p-values for regression equations that do not have trend terms.

According to the ADF test results, we can reject the null hypothesis of the presence of a unit root in the data series disregarding the specifications that are used for the regression equations (see Appendix G).

Overall, our tests indicate that all level (price) series have a unit root and all return series are stationary during both the stable and the crisis periods. In other words, all price series are integrated of order one, $I(1)$.

### *5.4 Tests for Cointegration*

"Don't put all eggs in the same basket!" Saavedra, (2000). This is a golden rule for risk management practices. Despite the well-known diversification benefits, in the real world, investors mainly invest in the domestic market, thus creating "home bias". The concept of home bias suggests that investors hold a lower-than-optimal share of their portfolio in foreign assets despite the fact that holding a larger share in foreign assets would decrease the risk and possibly increase returns (Lewis, 1999). In theory, investors have to invest in more than one stock market and pay attention to the linkages among the stock markets of interest to diversify the investment risk.

Taking into account the ongoing 2014–2015 Russian financial crisis, it is interesting to analyze whether there is a change in the long-run linkages between Russian, U.S. and EU stock markets. If the before-mentioned stock markets become more strongly correlated, diversification benefits will diminish. In our analysis, we will examine the cointegration of stock market indices during both the stable and the turmoil periods to evaluate the change in diversification benefits due to the mentioned crisis.

In the previous section, we used several approaches to determine the stationarity of log stock prices and returns. Taking into account that all of our price series are integrated of the same order, $I(1)$, we can perform Johansen's procedure to determine the number of cointegrating linkages among our variables.

#### 5.4.1 Lag length selection in VAR models

Before running the Johansen's cointegration tests, we should determine the appropriate number of lags and deterministic components in our regression equations. The choice of lag length depends on the Akaike and SBIC information criteria. If the AIC and the SBIC criteria provide contradictory results, the SBIC criterion is preferred due to the fact that it chooses a more parsimonious model.

**Table 5** 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 |

The results from the lag estimation of the VAR models that rely on regressing natural logarithm of stock index prices of all three stock markets during both the stable and the crisis periods are presented in Table 5. For the stable period (see Panel A), the AIC suggests a VAR model with three lags, but SBIC recommends using only two lags. The optimal number of lags for the stable period VAR model will be based on SBIC. During the crisis period, we follow the same rule of lag selection as during the stable period. Hence, the appropriate lag length during the turmoil period is two.

### 5.4.2 Deterministic components in the Johansen test- Pantula Principle

The results of estimating models 2-4 (see subsection 3.4.2) are presented in Table 6. Initially, we employ the Pantula Principle to test for cointegration of the price series. Starting with the most restrictive model during the stable period, the trace test statistic is 19.7694, which is less than the critical value of 32.2684 at 10% level. Hence, the null hypothesis of no cointegration cannot be rejected. This conclusion is supported by the results of both trace statistic and the maximum eigenvalue statistic. On the other hand, taking into account that all our stock index price series have intercepts and that most of the series follow a clear trend (see Graphs 3, 5), it is important that we test a model that has its deterministic components correctly specified (in this case it is the model 4) against the no cointegration hypothesis. Using maximum eigenvalue statistics, we can reject the null-hypothesis that the number of cointegrated relationships in our VAR model is 0 at 10% significance level, thus the alternative hypothesis, which suggests that the number of cointegrated vectors is one, is more preferred. In this case, there is a divergence between the results of the Pantula Principle and those obtained after assessing the plots of the series. Considering the evidence provided by Doornik et al. (1998), suggesting that an incorrect specification of deterministic components leads to loss in Johansen's test power, we prefer model 4 over model 2. In addition, considering that our sample size during the stable period is quite large and that the p-value from the maximum eigenvalue test is very close to 5%, we conclude that there is a cointegrating linkage between the prices of stock market indices that we analyze during the stable period.

During the crisis period the results of the Pantula Principle of no cointegration coincide with the results of the Model 4 for both likelihood tests that we use. Therefore, we conclude that there is no cointegrating relationship among stock markets that we analyze during the crisis period.

**Table 6** Pantula Principle. Trace statistic and maximum Eignemvalue statistic and their respective p-values, made by the authors using data from *Thomson Reuters Datastream*

| **Panel A**. Stable Period | | | | | | |
|---|---|---|---|---|---|---|
| | Model 2 | | Model 3 | | Model 4 | |
| N. of integration | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue |
| 0 | 19.7694 | 13.3013 | 29.7971 | 21.1316 | 42.9153 | 25.8232* |
| | (0.7410) | (0.5267) | (0.9438) | (0.8808) | (0.2396) | (0.0577) |
| 1 | 6.46807 | 4.060692 | 15.4947 | 14.2646 | 25.8721 | 19.3870 |
| | (0.9279) | (0.9542) | (0.9526) | (0.9277) | (0.9336) | (0.9014) |
| 2 | 2.40737 | 2.4074 | 3.8415 | 3.8415 | 12.5180 | 12.5180 |
| | (0.6960) | (0.6960) | (0.8878) | (0.8878) | (0.8995) | (0.8995) |
| **Panel B**. Crisis Period | | | | | | |
| | Model 2 | | Model 3 | | Model 4 | |
| N. of integration | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue |
| 0 | 21.4743 | 22.2996 | 29.7971 | 21.1316 | 42.9153 | 14.6486 |
| | (0.6308) | (0.8357) | (0.7450) | (0.8973) | (0.7622) | (0.6658) |
| 1 | 20.2618 | 15.8921 | 15.4947 | 14.2646 | 25.8721 | 19.3870 |
| | (0.4963) | (0.5753) | (0.5287) | (0.4650) | (0.8815) | (0.8672) |
| 2 | 9.16455 | 9.1646 | 3.84147 | 3.84147 | 12.5178 | 12.5178 |
| | (0.4568) | (0.4568) | (0.6399) | (0.6399) | (0.8218) | (0.8218) |

-MacKinnon-Haug-Michelis (1999) p-values
* indicates significance of results at 10% significance level

To conclude, our results suggest that there is no long-run association between the stock markets of the U.S., the EU and Russia after the 2014–2015 Russian crisis began, despite the fact that there was a cointegrating relationship between all three markets prior to the crisis. This suggests that the crisis period had an impact on the long-term linkage among the stock markets that we investigate. One implication from this result is that investors from these countries can reap greater benefits from diversification opportunities during the crisis, since markets do not move together towards a common equilibrium. In the next step, the Johansen test just summarizes the procedure performed above and presents a more in-depth analysis.

### 5.4.3 The Johansen approach

The results of Johansen cointegration test (see Table 7) 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.

**Table 7** Johansen cointegration test, made by the authors using data from *Thomson Reuters Datastream*

| | No. of int. vectors | Lag | Trace | Critical (at 10%) | Max-eigen. | Critical (at 10%) |
|---|---|---|---|---|---|---|
| **Panel A**. Stable Period | | | | | | |
| 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

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 Table 8).

**Table 8** Cointegrating relationships between *S&P 500, STOXX Europe 50* and *RTS* indices, made by the authors using data from *Thomson Reuters Datastream*

| | No. of int. vectors | Lag[A] | Trace | Max-Eigen |
|---|---|---|---|---|
| **Panel A**. Stable Period | | | | |
| 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).

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). In addition, our finding that there is a long-term linkage between equity markets of Russia and the

EU countries during the stable period is in line with the studies by Caporale and Spagnolo (2011) and Chittedi (2010). Moreover, there is evidence that the EU and U.S. stock markets were integrated prior to the 2014–2015 Russian crisis (Anaraki and Azad, 2009). The reasons why the above-mentioned equity markets became more interdependent during the stable period include the increase in trade among themselves, fast recovery from the subprime crisis, liberalization of capital flows, convergence in taxation of international capital investment and the decrease in investors' bias against foreign securities.

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. Chuhan (1994), Bekaert (1995) and Clare et al. (1995) suggest that changes in equity markets' linkages happen not only due to their liberalization, but also due to other factors such as information availability, investor protection, liquidity risks, political risk, currency risk and diverging/converging macroeconomic policies. We consider that both liquidity and currency risks increased significantly in Russia during the 2014–2015 crisis. Capital outflows in Russia peaked at $151.5 billion in 2014, up from $61 billion in 2013, thus exceeding the previous record of $133.6 billion set in 2008. In addition, FDI dropped by 50%, to $41 billion from $81 billion in 2014 (Weber, 2014). The Bank of Russia estimates that the capital outflow will be extremely large in 2015 (Grove, 2015). Accompanied by an increase of the illiquidity risk, the draught of capital might explain the lack of a long-run association between the Russian capital market and capital markets of the U.S. and EU. The currency risk is another reason for weaker long-run linkages with other stock markets The Russian ruble lost 50% of its value since the beginning of 2014. The two major factors that are considered to have contributed to the decrease in the ruble's price are the slump in the global oil prices, which dropped by around 50% in 2014 and the international sanctions imposed on Russia after it annexed Crimea and intervened in the Ukrainian conflict. Lower confidence in the ruble led to lower capital flows to Russia, thus weakening the linkages and the interdependence among global stock markets and Russian stock market, which consequently could have led to a disruption in the long-run linkages between Russian, the EU and U.S. stock markets.

A more surprising result is that the long-run association between the U.S. and EU stock markets has disappeared during the 2014–2015 Russian crisis. One of the reasons for this major change might be the increase of volatility and uncertainty in equity markets due to Russia' crisis and political tensions (e.g Russia/Ukraine, Greece etc.) which are on the rise (Tran et al., 2015). This could have had a significant impact on the risk-averse investors and financial institutions that are required to have a limited exposure to risky assets (Council of Mortgage Lenders, 2013). Another factor that could contribute to the weakening of the cointegration between the EU and U.S. capital markets is the divergence in monetary policies that their central banks have pursued (Khan, 2015). On 10 September 2014, European Central Bank (ECB) lowered all three key interest rates (ECB, 2014). The ECB lowered the interest rates in the money market, which, in turn, increased asset prices, including stock prices. In addition, the money market effect on the depreciating euro also stimulated asset prices by increasing profits of the EU companies from overseas, thus having a dual effect on stock market (ECB, n.d.). In addition, asset prices also increased due to quantitative easing (Kuttner and Mosser, 2002) that commenced in late October 2014 (Draghi, 2014). In addition, the Federal Reserve System (FRS) intends to increase its interest rates, thus shifting investor expectations and already incorporating the future interest rate increase in a stronger dollar, thus lowering asset prices in the U.S. (ECB, n.d.). This, in turn, increases stock market prices in Europe through an even weaker euro. Therefore, the diverging monetary policy effects could have led to a loss in the long-run equilibrium between the stock markets of the U.S. and EU. However, we would like to point out that the divergence in monetary policies of the U.S. and EU might not be the most significant factor making the long-run association between these countries' stock markets disappear because their monetary policies have been diverging since 2012 when the U.S. begun its third round of quantitative easing (Zumbrun, 2012).

To sum up, the results of the bi-variate Johansen cointegration tests expand on our previous findings by indicating 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.

### *5.5 Short-term linkages*

According to our results, there was a long-run linkage among equity markets of Russia, the U.S. and EU during the stable period, while we found no evidence of long-run association among the three capital markets during Russia's 2014–2015 crisis. It may be possible that two or more variables are not linked in the long-run, but there might be short-run causal 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 and whether there is a change in the Granger-causality linkages from one period to another. 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.

Initially, we will perform a Granger causality test to analyse short-term dynamic linkages between stock markets of our interest. As price series are cointegrated during the stable period and not cointegrated during the Russian crisis, we use a VECM model to perform a Granger causality test during the former period and a VAR model to perform a similar analysis during the latter time interval.

### 5.5.1 Lag length selection according to information criteria

Pairwise Granger causality tests are based on VAR and VECM models, thus we should initially decide on the number of lags we use in our models. Table 9 represents the choice of lag lengths. During the stable period, AIC suggests using a VAR (2) model, while SBIC suggests using a VAR (1) model. We prefer SBIC over AIC, thus we choose a VAR (1) model to perform the Granger causality test during the stable period. Due to similar reasons, we choose to have one lag for our independent variables in the VECM model.

**Table 9** 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 |

### 5.5.2 Return spillover effect: pairwise Granger causality tests

Table 10 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*.

During Russia's 2014-2015 crisis there are some changes in the short-term linkages among stock markets. One major change is that lagged *STOXX Europe 50* equity index returns are not statistically significant at predicting future returns of *S&P 500*. This implies that U.S. stock market prices are relatively immune to the pressure emerging in the EU stock market in the short-run, thus there are more short-run diversification opportunities for the ones who invest in the U.S. equity market. In addition, our results suggest that p-values of the hypotheses that *RTS* index returns do not Granger cause *S&P 500* and *STOXX Europe 50* returns decreased significantly during the crisis period. This indicates that the data for this period has a higher statistical power at reject the null hypotheses mentioned before. Thus *RTS* lagged returns are better at explaining future returns of *S&P 500* and of *STOXX Europe 50*. However, given that the highest significance level against which we compare our p-values is 10%, we still cannot reject the null hypothesis that *RTS* returns do not Granger cause other stock markets' returns. The following section features some of the reasons that explain the results described above.

The finding that the U.S. returns Granger cause other countries' returns can be explained by the fact that the U.S. has a developed equity market; therefore, it "exports" crises more than it "imports" them, thus acting like an engine of the global financial world (Menezes, 2013). Other studies also suggest that *S&P 500* is considered to have a dominant short-term impact on the returns of other stock market indices (Baumöhl and Výrost, 2010; Munteanu, et al., 2014).

Similarly to the U.S. stock market returns, the returns of the European stock market have a high statistical power at predicting returns of other stock markets, namely those of Russia and the U.S. equity markets, during the stable period. These short-run linkages during the stable period might be explained by the close ties among the capital markets of the countries mentioned above and by the high degree of development and high liquidity in the European stock market. It is worth mentioning that during Russia's 2014-2015 crisis the EU lagged returns do not Granger cause the U.S. equity market stock returns. An explanation for such a result might be the negative feedback from the Russian economy on the economies of the EU countries through less trade (considering that the EU is Russia's major trading partner), Greek legislative elections from January 2015 and their impact on the Euro/USD exchange (The Economist, 2015) and the ECB's quantitative easing programme that began in October 2014 (Draghi, 2014). An overall weaker euro, higher uncertainty in the Eurozone due to deepening debt crisis (Smith and Rankin, 2015), lower revenues of EU companies (due to the sanctions imposed on Russian enterprises) could have increased the uncertainty in the EU stock market, thus decreasing the statistical power of its returns to predict the returns of the U.S. raging bull stock market. On the other hand, the EU stock market returns can still predict Russian stock market returns due to the fact that the former is more developed (see Appendix H), thus it has a stronger ability to "export" different shocks.

The returns of the Russian stock market do not Granger cause any other stock markets' returns neither during the stable nor during the crisis periods. Even though we found evidence that during the crisis period the statistical power of lagged Russian stock index returns is higher at rejecting the null-hypothesis of no Granger causality, we still cannot reject the null hypothesis at 10% significance level. We have several explanations why the short-term linkages between Russia and other countries are weak. First, due to the fact that Russia is an emerging country, it is possible that the short-run return linkages between its stock market and other countries' stock markets are still rather weak. Second, Russia's 2014-2015 crisis is still ongoing; therefore, considering the pessimistic forecasts about the development of the Russian economy (Buckley, 2015; Grove, 2015), there might be statistically significant negative return spillover from Russia to the U.S. and to the EU equity markets in the future.

**Table 10** Granger causality test, made by the authors using data from *Thomson Reuters Datastream*

| Null-hypothesis: | F-statistic | Prob | Conclusion |
|---|---|---|---|
| **Panel A**. Stable Period | | | |
| 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

### 5.5.3 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 I 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. Next, we analyze Appendix I in more detail, and while describing the impact of shocks among stock markets we will mainly refer to their immediate effect.

Plot 1 depicts the response of returns of the Russian stock market due to a positive 1 standard deviation innovation/shock in each of the three equity markets during the stable period. As mentioned previously, the returns of Russia's stock market are mostly affected by shocks in its own market. In addition, they are positively affected by shocks in returns of the EU and U.S capital markets. It can be discernible that shocks in the EU stock market have relatively more impact on the returns of the Russian stock market than shocks from the U.S stock market during the stable period. One reason that would support these results is that the EU is Russia's major trading partner and its major investor (European Commission, 2014; BBC, 2014a) while the U.S. has relatively weaker ties with Russia. Overall, the return spillovers die out in around four periods.

Plot 2 depicts the response of returns of the Russian stock market due to a positive 1 standard deviation innovation/shock in each of the three equity markets during the crisis period. Similarly to the stable period, in the crisis period the Russian stock market is mostly affected by its own shocks, but the impact is much larger, which is consistent with the idea that the country faces a period of turmoil. An important change compared to the stable period is that shocks from the EU seem to have a relatively less significant impact on the Russian stock market than the shocks from the U.S., despite the fact that they were more influential during the stable period. One reason for this change might be the significant loss of trade opportunities due trade restrictions with the EU, which made the Russian economy less sensitive to changes in the economies of the EU countries. In addition, our results show that shocks in the returns from both the U.S. and EU are short-lived during the crisis period, which might be in line with the idea that sanctions overall, could have made Russian equity markets more isolated and less sensitive to changes in foreign equity markets.

Plots 3 and 4 present the response of the returns of the U.S. stock market to a positive 1 standard deviation innovation/shock in each of the three equity markets during the stable and crisis periods respectively. Similarly to the case of Russia, innovations of the U.S. stock market have a larger impact on future U.S. returns than the innovations from the EU or Russia. Innovations from the EU stock market seem to have a more significant impact on the returns of the U.S. equity market, than innovations from Russian stock market. An explanation for this result is that the EU is the largest trade partner of the U.S. (U.S. Census Bureau, 2015) and it is also its primary investment partner (OECD Observer, 2015).

Plots 5 and 6 show the response of returns of the EU stock market to a positive 1 standard deviation innovation/shock in each of the three equity markets during the stable and crisis periods respectively. Prior to the crisis, the U.S. and Russian equity market return innovations had almost a similar impact on the future EU stock market returns in the following period; however, the impact of the Russian stock market shocks seem to be less significant than the shock from the U.S. equity market after the crisis. This change can be explained by the diminished trade volume between the EU and Russia (World Bulletin, 2015). The persistence/duration of return spillovers from all three countries' stock markets on the equity market of the EU did not undergo a significant change during the crisis period.

### 5.5.4 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 J are discussed below.

Plots 1 and 2 show that that the variance of the returns of the U.S. stock market is not explained by return innovations in the EU and Russian stock markets. Also, the extent to which variance of the U.S. equity market returns is explained by shocks in other markets did not change during the Russian crisis period. As we stated previously, an explanation for such a result is that the U.S. has a relatively more developed stock market; therefore, it is more likely to send shocks to other countries than to receive them from other countries (Menezes, 2013).

Plots 3 and 4 from the same Appendix depict the variance of returns of the EU stock market due to shocks in the Russian, the EU and the U.S. stock markets during the stable and the crisis period respectively. During the stable period, on average around 70% of the variance of the EU stock market returns could be explained by shocks which occurred within the EU stock market and 30% of the variance of the EU equity market is explained by the shocks which occurred in the U.S. capital market.  During the crisis period, the impact on the EU equity markets of the shocks originating in the U.S. stock market is lower that it was during the stable period, while the impact on its own shocks has a larger effect on the volatility of the EU stock market returns. A potential explanation for such a result is that it is not only Russia which became more isolated after trade linkages with the EU weakened, but it is also the EU which lost trade opportunities and became more separated from other countries due to lower income, which can be translated into lower investment and trade opportunities with other countries. Considering that the EU trades eleven times more goods and services with Russia than the U.S. does, weaker trade linkages are considered to be more dangerous for the EU member countries (Traynor, 2014). Movements in the Russian stock market seem to have an insignificant impact on the variance of returns of the EU equity market during both the stable and crisis periods. In this case, we can state that the EU has a relatively larger stock market (Appendix H), thus it is more likely to influence other markets through own shocks than to be influence by foreign shocks.

Plots 5 and 6 present the variance of the returns of the Russian stock market due to shocks in the Russian, the EU and U.S. stock markets during the stable and crisis periods respectively. During the stable period innovations in returns from the stock markets of the U.S. and EU explained a similar proportion of the variation in returns of the Russian equity market (~20%). However, during the crisis period, shock in returns from the EU capital markets seem be able to explain less of the volatility of the Russian stock market, which is consistent with our idea that Russia became more isolated from the EU due to trade barriers.

Overall, our tests on short-run linkages among stock markets suggest that the EU equity 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 between these stock markets prior to the crisis. In addition, we found that the statistical power of the Russian equity market returns to Granger-cause returns of the U.S. and the EU equity markets increased significantly during the crisis, but we the p-value is still not low enough to reject the null-hypothesis of no Granger causality between Russia and the above-mentioned countries.

Using general impulse functions, we identified that shocks among the three markets had a positive impact on each other during both stable and crisis periods and that own shocks had a larger impact on stock markets returns than foreign return innovations. The same analysis suggests that 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.

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.

### *5.6 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 function used to estimate the GARCH-BEKK model is presented in Appendix K. The estimated coefficients of the innovation and lagged variance-covariance parameters during the stable and the crisis periods are presented in the Appendix L.

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 L). 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 L, 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 M). 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 L) 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 (see Graph 2, Appendix A). Thus, this channel of transmission of volatility could have been practically inactive

Overall, our results suggest that a few new shock spillover and volatility spillover linkages appeared during the Russian crisis, while the existing ones intensified; hence they became more statistically significant. Also, it seems that Russian equity market was very active at impacting the volatility of other stock markets through shock and volatility spillovers during the crisis period. Because the Russia's 2014-2015 crisis was captured by other stock markets through shock and volatility spillovers which were transported through the variance equation, this serves as evidence of a contagion effect between the Russian equity market and the stock markets of the U.S. and EU during the Russia's 2014-2015 crisis.

## 6 ROBUSTNESS TEST

To test the robustness of our results, we used another volatility indicator, namely, the annualized daily historical volatility that we calculated using *RTS* index returns. Similarly to the time span of the *RTS Volatility* Index, the time span of the historical volatility is from 10 January 2006 until 3 March 2015. The Bai-Perron structural break test on the historical volatility of the *RTS* index indicates that the Russia's 2014-2015 financial crisis started on 28 February, which is one trading day earlier than the date we found using the *RTS Volatility* Index. On the other hand, according to the historical volatility, the stable period started on 9 October 2012, which is five trading days later than the date suggested by the *RTS Volatility* Index. After finding that the series is stationary (see Appendix N), we performed the same analysis as before using new time periods for the stable and the crisis periods. Overall, our results support our conclusion that the long-run linkage between the stock markets of the EU, U.S. and Russia disappeared during the crisis period (see Appendix O). In addition, all our results regarding the changes in the short-term linkages between these stock markets are confirmed (see Appendices P,Q,R). Moreover, the results of the GARCH-BEKK model using historical volatility imply higher volatility spillover from the Russian stock market during the crisis period than we previously identified, thus our conclusion that there exists a contagion effect during the Russia's crisis is corroborated.

## 7 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.

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. 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.

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. By performing a bivariate analysis, we found that there is no long-run linkage between any two of the three countries during the crisis. 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.

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. 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. 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.

Our impulse response analysis suggests that return innovations from each market have a positive impact on other markets' future returns. 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. 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. 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. 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. 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. 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.

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. 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. 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. 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.

## 8 IMPLICATIONS

The Johansen cointegration test results suggest that there is no cointegrating relationship among any of the stock markets that we analyzea during the crisis period, even if there was a cointegration linkage prior to the crisis. These results indicate that U.S. investors can reap long-run benefits from diversification opportunities by investing in the equity markets of Russia, the U.S. and EU, since these equity markets do not move in the long-run towards a common equilibrium. This information may be useful to private and institutional investors, as well as financial institutions who invest in the equity markets of the countries that we investigate.

The results of the Granger causality test suggest that the short-run linkage between the EU and U.S. stock markets vanished during the crisis period; therefore, there is no short-run pressure on the U.S. stock market prices emerging from the EU stock market prices. This indicates that the U.S. stock market is independent from changes in the EU stock market price in the short-run, so there are short-run diversification opportunities for investors who wish to invest in the U.S. stock market.

Conclusions regarding the efficiency of the analyzed stock markets are diverging. The Johansen cointegration test suggests that stock markets were not weak-form efficient during the stable period, since it was possible to predict the direction of stock index prices of one market by analyzing the long-term trend of prices in other markets, while they are weak-form efficient after the crisis, since there is no cointegration relationship between the stock markets of Russia, the U.S. and EU. On the other hand, the Granger-causality test suggests that it is possible to use past returns of one market to predict future returns of another market during both the crisis and stable periods; therefore, stock markets that we analyze are not weak-form efficient.

Considering the results of our GARCH-BEKK model, cross-volatility among the EU, U.S. and Russia is significantly influenced by shock and volatility spillovers transferred from other countries and particularly from Russia during the crisis period. This information should be useful in computing option prices and building Value-at-Risk (VaR) models to individuals and institutions investing in the equities of these countries. In addition, given that the contagion effect was found among the analyzed countries' stock markets, official institutions should enact policies that would strengthen economies and financial markets during periods of turmoil. An interesting way to reduce countries' exposure to contagion from other countries is to let them issue growth-indexed bonds. These particular financial securities link payments on sovereign debt to the issuing state's GDP growth rate. These securities' aim is to reduce economic volatility and sustain government resources, since the government is not forced to reduce spending when the economic growth is low and it is required to limit its spending when the growth is high (Borensztein & Mauro, 2004). By stabilizing debt payments, growth-indexed bonds can decrease the probability of crises. Furthermore, another more global approach to limit economic volatility is to decrease the effect of contagion by refining sovereign-debt restructuring mechanisms (Roubini & Setser, 2004). Defining and clarifying the procedure by which countries restructure their debt could significantly reduce losses to investors and to countries, and by reducing these risks, there should be less contagion during crises.

# 9 LIMITATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

The GARCH-BEKK model that we use to analyze the volatility and shock spillovers among equity markets assumes that negative and positive shocks have an equal impact on the own and cross-country volatility; however, this is not always the case. To circumvent the asymmetry in the response of conditional volatilities and correlations to negative return innovations across markets, we suggest using an asymmetric multivariate GARCH model. We could not perform such an analysis due to time restrictions related to writing this paper.

In addition, it would be truly interesting to broaden our analysis by performing the same tests on each EU member state separately. This would provide a more comprehensive view about investment decisions, as well as shock and volatility spillover effects from the Russia's 2014-2015 crisis.

Taking into account that one of our findings is that shock and volatility spillover effects strengthened during the crisis, it would be very compelling to identify channels of transmission of contagion among analyzed equity markets during this crisis period.

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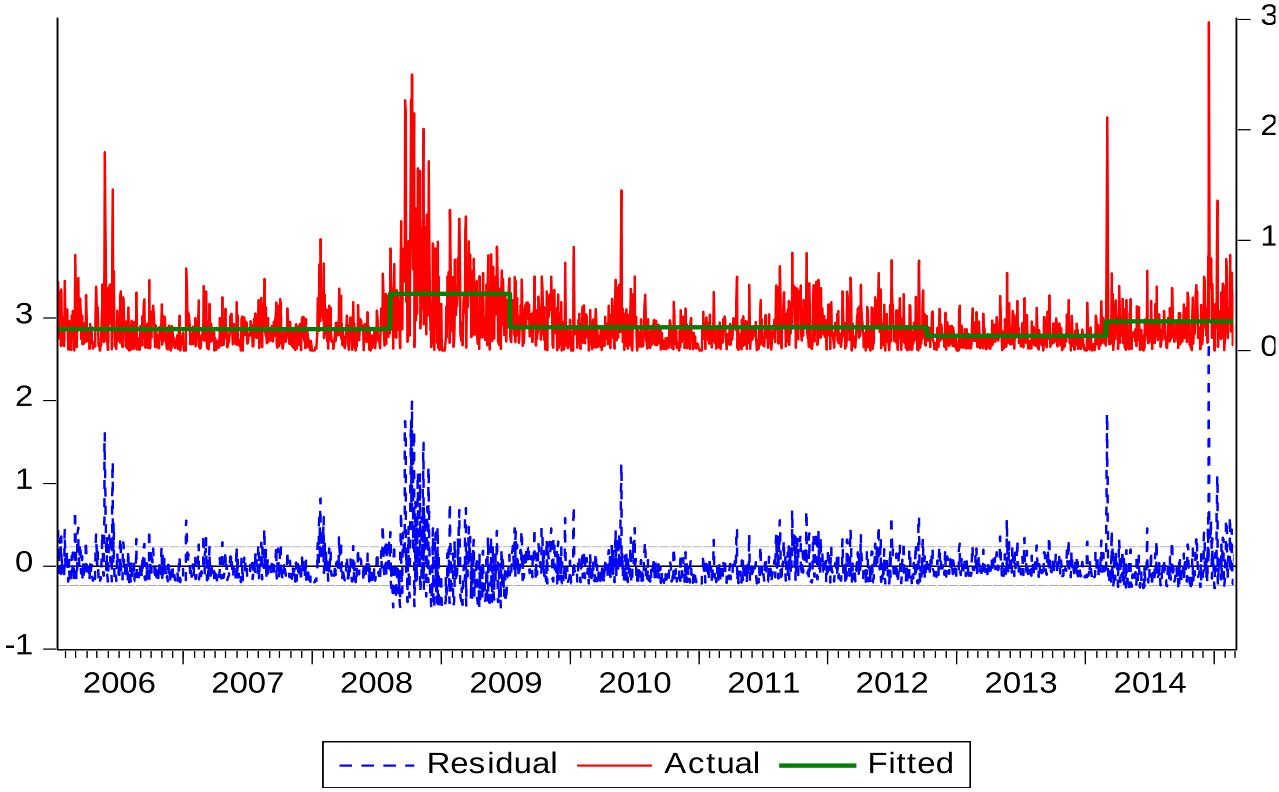
## APPENDICES

**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** - Historical volatility break-periods, graphical representation, 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 |
|---|---|---|
| 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 D** - Unit root tests for stock market indices in levels and their respective p-values during the stable period**,** made by the authors using data from *Thomson Reuters Datastream*

| | *t-statistic* | | *LM-Statistic* | |
|---|---|---|---|---|
| | ADF | | KPSS | |
| Stock index | Intercept | Trend and intercept | Trend | Trend and intercept |
| S&P 500 | -0.5022 | -3.6436** | 3.1558*** | 0.1728** |
| | (0.8876) | (0.0276) | | |
| STOXX Europe 50 | -0.8527 | -3.4309** | 2.8451*** | 0.2231*** |
| | (0.6492) | (0.049) | | |
| RTS | -1.3966 | -1.8102 | 0.9914*** | 0.2465*** |
| | (0.5843) | (0.6980) | | |

*, ** and *** indicate significance of results at 10%, 5% and 1% significance level, respectively. Automatic lag length selection using SBIC information criterion.
Null hypothesis KPSS: Series is stationary.
Null hypothesis ADF: Series has unit root
Sample period: 02 October 2012 to 28 February 2014. Number of observations 369.

**Appendix E** - Unit root tests on returns of the three stock market indices with their respective p-values during the stable period**,** made by the authors using data from *Thomson Reuters Datastream*

| | *t-statistic* | | | *LM-Statistic* | |
|---|---|---|---|---|---|
| | ADF | | | KPSS | |
| Stock index | None | Intercept | Trend and intercept | Trend | Trend and intercept |
| S&P 500 | -10.824*** | -10.802*** | -10.779*** | 0.270 | 0.319*** |
| | (0.000) | (0.000) | (0.000) | | |
| STOXX Europe 50 | -14.506*** | -14.486*** | -14.466*** | 0.408 | 0.329*** |
| | (0.000) | (0.000) | (0.000) | | |
| RTS | -12.606*** | -12.589*** | -12.574*** | 0.062 | 0.062 |
| | (0.000) | (0.000) | (0.000) | | |

*,** and *** indicate significance of results at 10%, 5% and 1% significance level, respectively. Automatic lag length selection using SBIC information criterion.
Null hypothesis KPSS: Series is stationary.
Null hypothesis ADF: Series has unit root
Sample period: 02 October 2012 to 28 February 2014. Number of observations 369.

**Appendix F** - Unit root tests for stock market indices in levels and their respective p-values during the crisis period, made by the authors using data from *Thomson Reuters Datastream*

| | *t-statistic* | | *LM-Statistic* | |
|---|---|---|---|---|
| | ADF | | KPSS | |
| Stock index | Intercept | Trend and intercept | Trend | Trend and intercept |
| S&P 500 | -1.4754 (0.5447) | -3.3036* (0.0679) | 1.7687*** | 0.1867*** |
| STOXX Europe 50 | -1.2880 (0.6357) | -2.6359 (0.2648) | 1.9409*** | 0.2494*** |
| RTS | -0.8825 (0.7928) | -0.8702 (0.7965) | 1.8121*** | 0.4442*** |

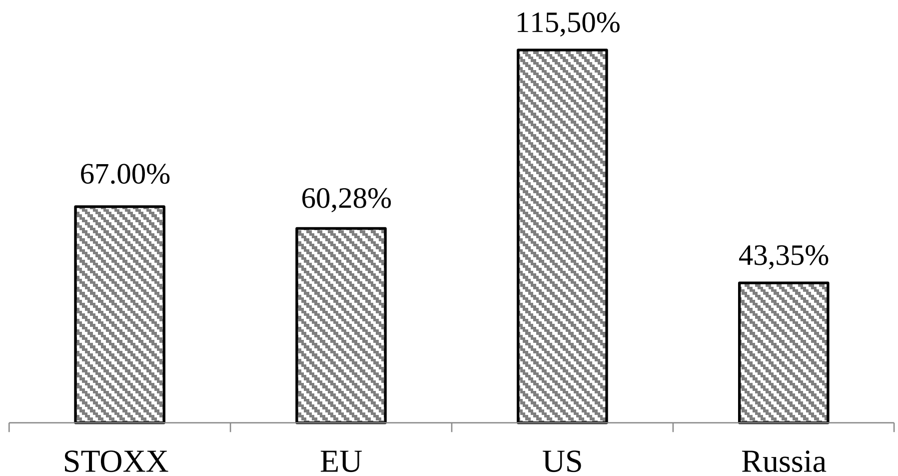
*, ** and *** indicate significance of results at 10% , 5% and 1% significance level, respectively. KPSS test does not provide any p-value.
Automatic lag length selection using SBIC information criterion.
Null hypothesis KPSS: Series is stationary.
Null hypothesis ADF: Series has unit root
Sample period: 03 March 2014 to 03 March 2015. Number of observations 262.

**Appendix G** - Unit root tests on return of the three stock market indices and their respective p-values during the crisis period, made by the authors using data from *Thomson Reuters Datastream*

| | *t-statistic* | | | *LM-Statistic* | |
|---|---|---|---|---|---|
| | ADF | | | KPSS | |
| Stock index | None | Intercept | Trend and intercept | Trend | Trend and intercept |
| S&P 500 | -10.8237*** (0.000) | -10.8017*** (0.000) | -10.7800*** (0.000) | 0.2698 | 0.1748** |
| STOXX Europe 50 | -11.8287*** (0.000) | -11.8042*** (0.000) | -10.7792*** (0.000) | 0.4571 | 0.1740** |
| RTS | -13.3759*** (0.000) | -13.3496*** (0.000) | -13.3222*** (0.000) | 0.3152 | 0.1776** |

* , ** and *** indicate significance of results at 10%, 5% and 1% significance level, respectively. Automatic lag length selection using SBIC information criterion.
Null hypothesis KPSS: Series is stationary.
Null hypothesis ADF: Series has unit root
Sample period: 03 March 2014 to 03 March 2015. Number of observations 262.

**Appendix H** – Market capital to GDP ratio (in percent for 2012), made by the authors using data from *Thomson Reuters Datastream* and *Eurostat* (2015)

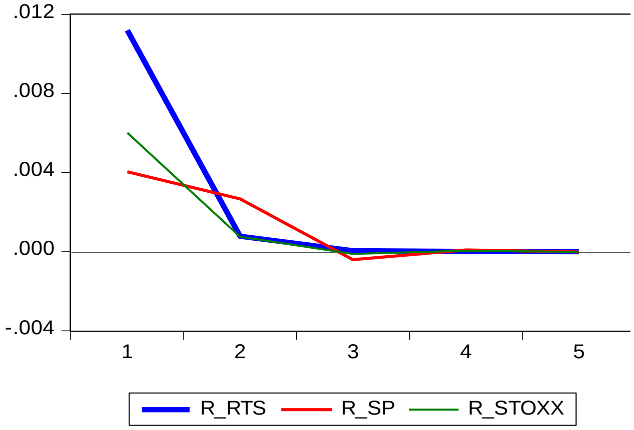



We used two data sets to calcualte the ratio of Europe's stock market capitalization-to-GDP. The first one computes the stock market-to-GDP ratio of all 28 member states of the European Union, whereas the second data set replicates the countrie that are in the STOXX Europe 50 index. Note that this index includes only the biggest countries in Europe and two non-EU countires: Norway and Switzerland. In total of 18 countries. For both cases, all individual country market capitalization and GDPs were added together and divided one by another (see EU and STOXX stack in the chart above). In both cases EU stock market-to-GDP ratio is larger than stock market-to-GDP of Russia, but lower than that of the U.S.

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

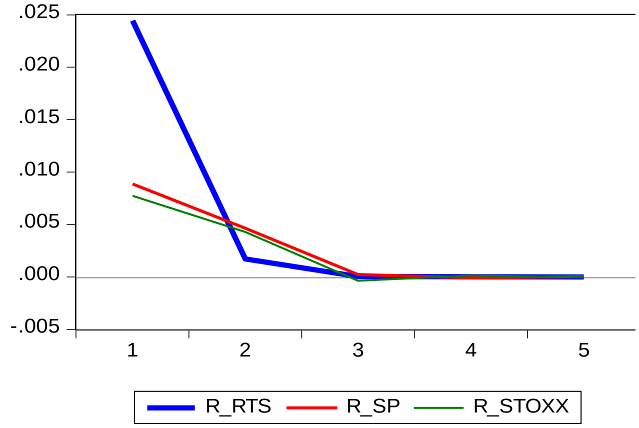
Stable period

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

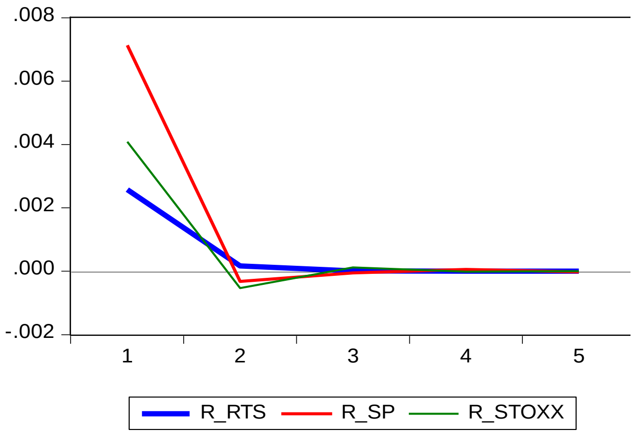



Crisis period

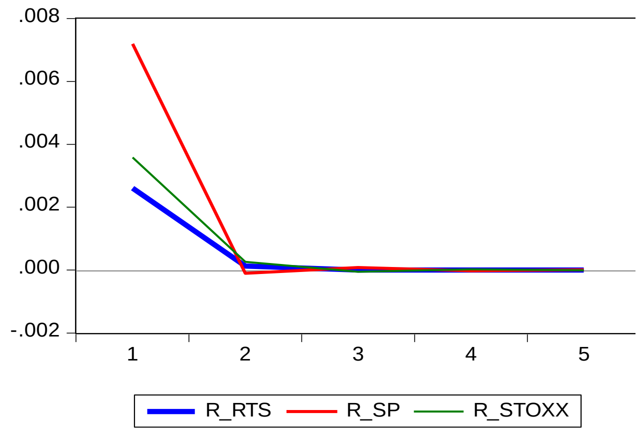
Response of R_RTS to Generalized One S.D. Innovations (Plot 2)



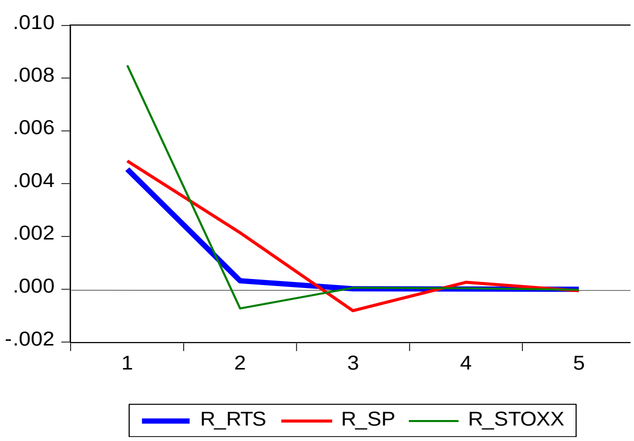

Response of R_SP to Generalized One S.D. Innovations (Plot 3)



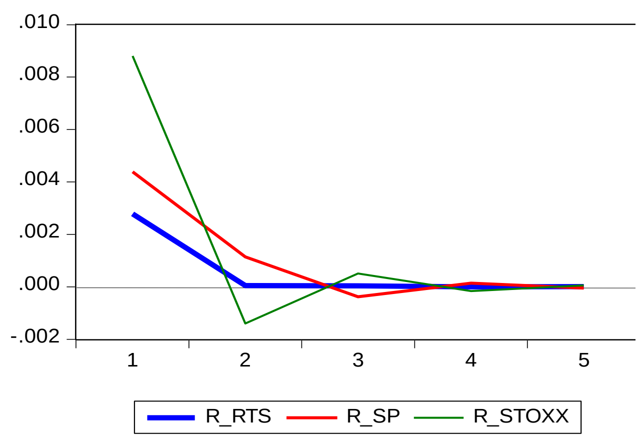

Response of R_SP to Generalized One S.D. Innovations (Plot 4)




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

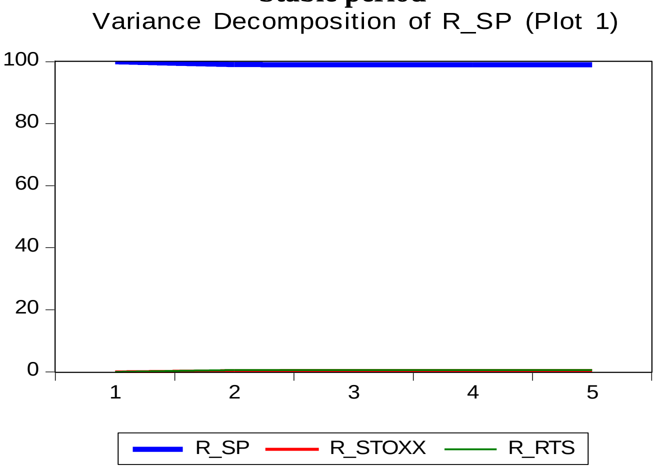



Response of R_STOXX to Generalized One S.D. Innovations (Plot 6)

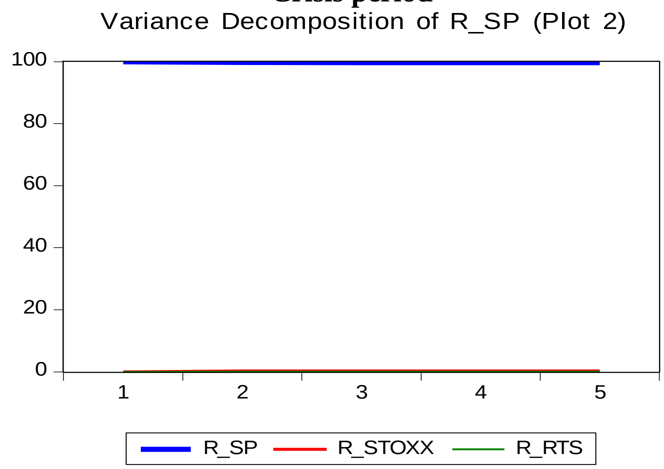


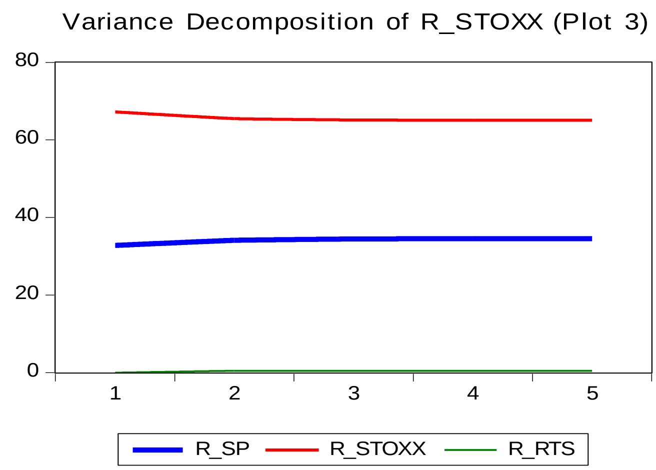
**Appendix J -** Variance decomposition analysis during the stable period and during the Russian crisis periods, made by the authors using data from *Thomson Reuters Datastream*

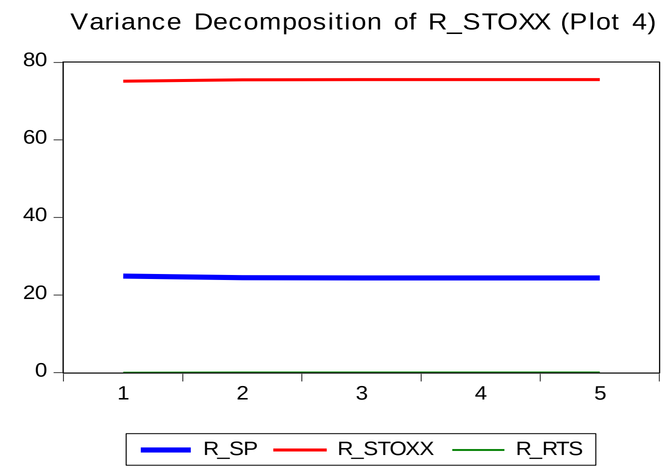
**Stable period**

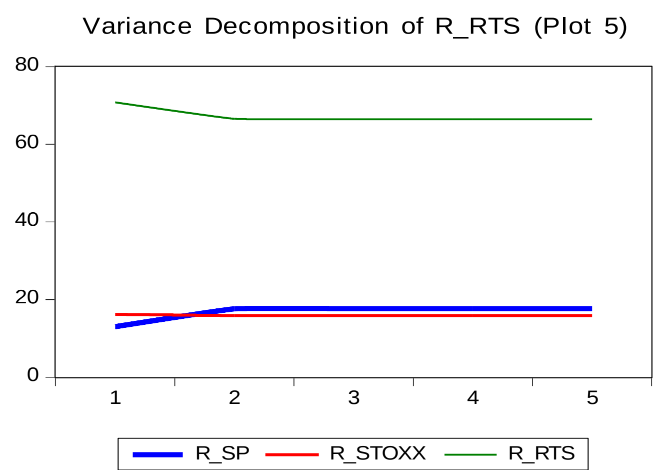


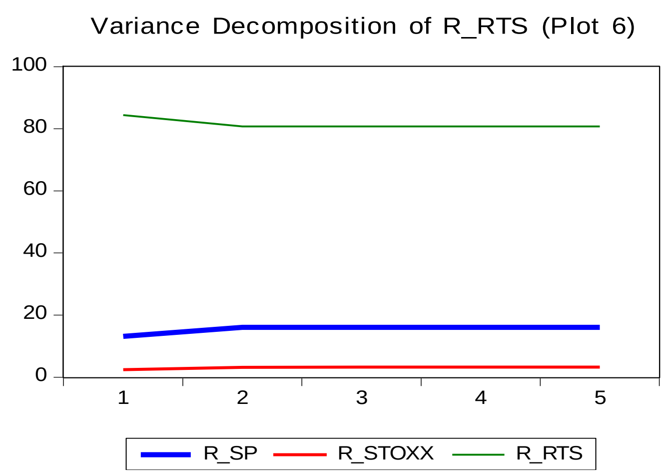

**Crisis period**



**Appendix K** – fully-parameterized VAR-BEKK model code in R (GitHub, n.d.), adjusted by the authors

```
##' @import mvtnorm
##' @import tseries
##' @export
mvBEKK.est<-
function(
			eps,
			order  = c(1,1),
			params = NULL,
			fixed  = NULL,
			method = "BFGS",
			verbose = F
		)
{
  count.triangular <-
    function(dimension){
      if(dimension <= 0){
        0
      }
      else{
        dimension + count.triangular(dimension - 1)
      }
    }

  if(verbose == T){
    out <- function(...){
      cat(...)
    }
  }
  else{
    out <- function(...) { }
  }
	series.length = length(eps[,1])
	series.count  = length(eps[1,])
	if(order[1] != as.integer(order[1]) || order[2] != as.integer(order[2]))
	{
		stop("order property should contain integer values")
	}
	if(order[1] < 0 || order[2] < 1)
	{
		stop("BEKK(",order[1],",",order[2],") is not implemented.")
	}
	params.length = count.triangular(series.count) + (order[2] * series.count^2) + (order[1] * series.count^2)
	if(is.null(params))
	{
		params = c(1,0,1,0,0,1)
		params = c(params, rep(0.1, params.length - 6))
		out("\nWarning: initial values for the parameters are set to:\n\t", params,"\n")
	}
	else if(length(params) != params.length)
	{
		stop("Length of the initial parameter list doesn't conform required length. There should be ",
params, " parameters in total")
	}
	if(!is.null(fixed))
```

```
	{
		if(
				(!is.array(fixed)) ||
				(dim(fixed)[1] != 2) ||
				(length(fixed[1,]) != length(fixed[2,])))
		{
			stop("fixed should be an array of two vectors. Try fixed = array(c(a,b,c,d,...), dim = 
c(2,y))")
		}
		for(count in 1:length(fixed[1,]))
		{
			if((fixed[1,count] != as.integer(fixed[1,count])) || (fixed[1,count] <= 0))
			{
				stop("First dimension of the fixed array should contain only positive integer 
values for indexing purposes")
			}
		}
		if(length(fixed[1,]) > length(params))
		{
			stop("fixed array could not contain more index-value pairs than the params array 
length");
		}
	}
	if(!(
		(method == "Nelder-Mead") ||
		(method == "BFGS") ||
		(method == "CG") ||
		(method == "L-BFGS-B") ||
		(method == "SANN")
		))
	{
		stop("'", method, "' method is not available")
	}
	fake.params = params
	if(!is.null(fixed))
	{
		fake.params = params
		for(i in 1:length(fixed[1,]))
		{
			fake.params[fixed[1,][i]] = NA
		}
		fake.params = na.omit(fake.params)
	}
	loglikelihood.C <- function(params)
	{
		loglikelihood.C <- .C("loglikelihood",
			as.vector(params, mode = "double"),
			as.vector(fixed[1,], mode = "integer"),
			as.vector(fixed[2,], mode = "double"),
			as.integer(length(fixed[1,])),
			as.vector(t(eps)),
			as.integer(series.count),
			as.integer(series.length),
			as.vector(order, mode = "integer"),
			retval = 0.0,
			PACKAGE = "mgarch"
		)
		if(is.nan(loglikelihood.C$retval) == T)
```

```
		{
			nonusedret = 1e+100
		}
		else
		{
			nonusedret = loglikelihood.C$retval
		}
		nonusedret
	}
	start = Sys.time()
	out("* Starting estimation process.\n")
	out("* Optimization Method: '", method, "'\n")
	estimation = optim(fake.params, loglikelihood.C, method = method, hessian = T)
	out("* Estimation process completed.\n")
	est.time = difftime(Sys.time(), start)
	aic = estimation$value + (length(params) - length(fixed[1,]))
	if(length(fake.params) == 0)
	{
		estimation$hessian = matrix(rep(0.1, series.count^2), nrow = series.count, ncol = series.count)
	}
	inv.hessian.mat = solve(estimation$hessian)
	diag.inv.hessian = sqrt(abs(diag(inv.hessian.mat)))
	if(length(which(diag(inv.hessian.mat) < 0)) == 0)
	{
		warning("negative inverted hessian matrix element")
	}
	if(!is.null(fixed))
	{
		temp.diag.inv.hessian = numeric()
		shifted = 0
		for(count in 1:params.length)
		{
			check.point = 0
			for(i in 1:length(fixed[1,]))
			{
				if(count == fixed[1,i])
				{
					check.point = 1
					shifted = shifted + 1
					temp.diag.inv.hessian[count] = 0
					break
				}
			}
			if(check.point == 0)
			{
				temp.diag.inv.hessian[count] = diag.inv.hessian[count - shifted]
			}
		}
		diag.inv.hessian = temp.diag.inv.hessian
	}
	parnum = 1 + order[1] + order[2]
	asy.se.coef = list()
	tmp.array = array(rep(0, series.count^2), dim = c(series.count, series.count))
	tmp.array[!lower.tri(tmp.array)] = diag.inv.hessian[1:length(which(!lower.tri(tmp.array) == T))]
	asy.se.coef[[1]] = tmp.array
	for(count in 1:(parnum - 1))
	{
		asy.se.coef[[count + 1]] = array(diag.inv.hessian[(count.triangular(series.count) + 1 + (count - 1) *
```

```
series.count^2):(count.triangular(series.count) + 1 + series.count^2 + (count - 1) * series.count^2)], dim =
c(series.count, series.count));
	}
	buff.par = list()
	if(!is.null(fixed))
	{
		estim.params = numeric()
		shifted = 0
		for(count in 1:params.length)
		{
			check.point = 0
			for(i in 1:length(fixed[1,]))
			{
				if(count == fixed[1,i])
				{
					check.point = 1
					shifted = shifted + 1
					estim.params[count] = fixed[2,i]
					break
				}
			}
			if(check.point == 0)
			{
				estim.params[count] = estimation$par[count - shifted]
			}
		}
	}
	else
	{
		estim.params = estimation$par
	}
	tmp.array = array(rep(0, series.count^2), dim = c(series.count, series.count))
	tmp.array[!lower.tri(tmp.array)] = estim.params[1:length(which(!lower.tri(tmp.array) == T))]
	buff.par[[1]] = tmp.array
	for(count in 1:(parnum - 1))
	{
		buff.par[[count + 1]] = array(estim.params[(count.triangular(series.count) + 1 + (count - 1) *
series.count^2):(count.triangular(series.count) + 1 + series.count^2 + (count - 1) * series.count^2)], dim =
c(series.count, series.count));
	}
	buff.par.transposed = lapply(buff.par, t)
	out("* Starting diagnostics...\n")
	out("* Calculating estimated:\n")
	out("*\t1. residuals,\n")
	out("*\t2. correlations,\n")
	out("*\t3. standard deviations,\n")
	out("*\t4. eigenvalues.\n")
	HLAGS = list()
	for(count in 1:order[1])
	{
		HLAGS[[count]] = array(rep(0, series.count^2), dim = c(series.count,series.count))
		diag(HLAGS[[count]]) = 1
	}
	residuals = list()
	for(i in 1:series.count)
	{
		residuals[[i]] = numeric()
	}
```

```
for(count in 1:max(order))
{
	for(i in 1:series.count)
	{
		residuals[[i]][count] = 0
	}
}
resid = array(rep(0,series.count), dim = c(series.count,1))
temp = 0
for(count in 2:parnum)
{
	temp = temp + kronecker(buff.par[[count]], buff.par[[count]])
}
eigenvalues = svd(temp)$d
numerat = t(buff.par[[1]]) %*% buff.par[[1]]
dim(numerat) = c(series.count^2,1)
denom = solve(diag(rep(1, series.count^2)) - temp)
sigma = denom %*% numerat
dim(sigma) = c(series.count, series.count)
H = cov(eps)
H.estimated = lapply(1:series.length, function(x){H})
cor = list()
for(i in 1:series.count)
{
	cor[[i]] = list()
	for(j in 1:series.count)
	{
		cor[[i]][[j]] = numeric()
	}
}
sd = list()				for(i in 1:series.count)
{
	sd[[i]] = numeric()
}
eps.est = array(rep(0,series.count), dim = c(series.count,1))
CTERM = buff.par.transposed[[1]] %*% buff.par[[1]]
out("* Entering Loop...");
for(count in (max(order) + 1):series.length)
{
		if(order[1] >= 2)
	{
		for(tmp.count in order[1]:2)
		{
			HLAGS[[tmp.count]] = HLAGS[[(tmp.count - 1)]]
		}
	}
	HLAGS[[1]] = H
	H = CTERM
	ord1 = 1
	for(tmp.count in 1:(order[2] + order[1]))
	{
		if(tmp.count <= order[2])
		{
				H = H + buff.par.transposed[[tmp.count + 1]] %*%
as.matrix(t(eps[count - tmp.count,])) %*% as.matrix(eps[count - tmp.count,]) %*% buff.par[[tmp.count + 1]]
		}
		else
		{
```

```
				H = H + buff.par.transposed[[tmp.count + 1]] %*% HLAGS[[ord1]]  %*% buff.par[[tmp.count + 1]]
				ord1 = ord1 + 1
			}
		}
		H.estimated[[count]] = H
		svdH = svd(H)
		sqrtH = svdH$u %*% diag(sqrt(svdH$d)) %*% t(svdH$v)
		invsqrtH = solve(sqrtH)
		resid = invsqrtH %*% as.matrix(t(eps[count,]))
		for(i in 1:series.count)
		{
			residuals[[i]][count] = resid[i,1]
		}
		for(i in 1:series.count)
		{
			for(j in 1:series.count)
			{
				cor[[i]][[j]][count] = H[i,j] / sqrt(H[i,i] * H[j,j])
			}
		}
		for(i in 1:series.count)
		{
			sd[[i]][count] = sqrt(H[i,i])
		}
	}
	out("Diagnostics ended...\n")
	names(order) <- c("GARCH component", "ARCH component")
	names(buff.par) <- as.integer(seq(1, parnum))
	mvBEKK.est <- list(
		eps = eps,
		series.length = series.length,
		estimation.time = est.time,
		total.time = difftime(Sys.time(), start),
		order = order,
		estimation = estimation,
		aic = aic,
		asy.se.coef = asy.se.coef,
		est.params = buff.par,
		cor = cor,
		sd = sd,
		H.estimated = H.estimated,
		eigenvalues = eigenvalues,
		uncond.cov.matrix = sigma,
		residuals = residuals
	)
	class(mvBEKK.est) = "mvBEKK.est"
	out("Class attributes are accessible through following names:\n")
	out(names(mvBEKK.est), "\n")
	return(mvBEKK.est)
}
```

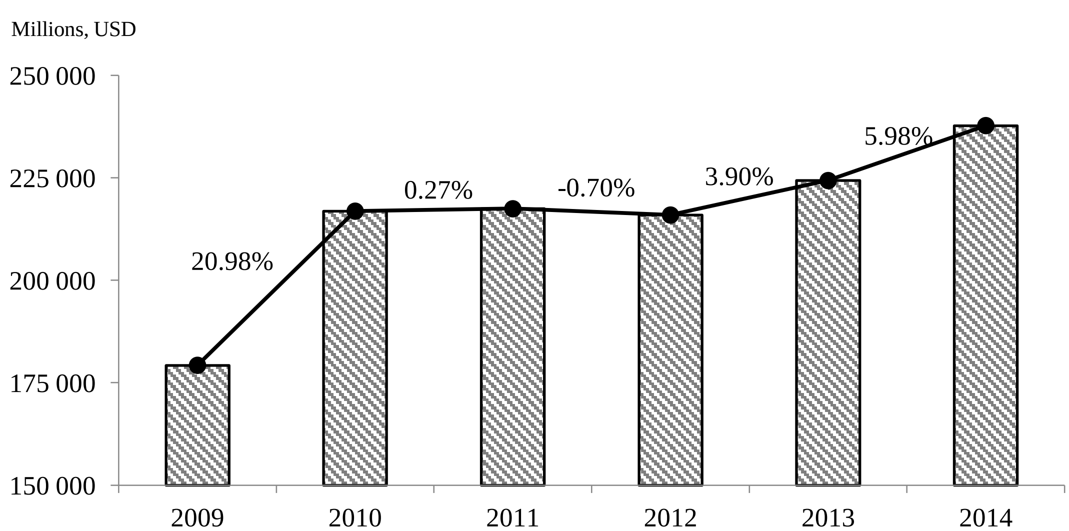
This R function is a part of the MGARCH package that was developed by Harald Schmidbauer <harald@hs-stat.com>, Angi Roesch <angi@angi-stat.com> and that can be freely distributed. We would like to thank both authors for their useful advice during the code assessment and adjustment process.

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



**Appendix N** – Annualized daily volatility: Unit root test, made by the authors using data from *Thomson Reuters Datastream*

| | ADF | | KPSS |
|---|---|---|---|
| Constant | -11.5575*** | Constant | 0.3237 |
| Constant & trend | -11.7297*** | Constant& trend | 0.0814 |

*,** 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 O** – Annualized daily volatility: Cointegration test, made by the authors using data from *Thomson Reuters Datastream*

| Panel A. Stable Period | | | | | | |
|---|---|---|---|---|---|---|
| | Model 2 | | Model 3 | | Model 4 | |
| N. of integration | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue |
| 0 | 21.3615 | 14.4095 | 12.1774 | 8.3267 | 34.0149 | 24.3695* |
| | (0.6383) | (0.4252) | (0.9255) | (0.8826) | (0.2878) | (0.0768) |
| 1 | 6.9520 | 4.4341 | 3.8508 | 3.5715 | 9.6454 | 7.2354 |
| | (0.9003) | (0.9318) | (0.9125) | (0.9016) | (0.9392) | (0.8841) |
| 2 | 2.5179 | 2.5179 | 0.2793 | 0.2793 | 2.4100 | 2.4100 |
| | (0.6740) | (0.6740) | (0.5972) | (0.5972) | (0.9380) | (0.9380) |
| Panel B. Crisis Period | | | | | | |
| | Model 2 | | Model 3 | | Model 4 | |
| N. of integration | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue | Trace-stat | Eigenvalue |
| 0 | 21.1541 | 9.7428 | 14.9985 | 7.6292 | 25.0434 | 14.8325 |
| | (0.6521) | (0.8546) | (0.7802) | (0.9249) | (0.7876) | (0.6495) |
| 1 | 11.4113 | 7.6042 | 7.3693 | 7.1049 | 10.2109 | 7.1101 |
| | (0.5029) | (0.5955) | (0.5351) | (0.4768) | (0.9157) | (0.8931) |
| 2 | 3.8071 | 3.8071 | 0.2644 | 0.2644 | 3.1008 | 3.1008 |
| | (0.4416) | (0.4416) | (0.6071) | (0.6071) | (0.8643) | (0.8643) |

-MacKinnon-Haug-Michelis (1999) p-values
*- indicates significance of results at 10% significance level
Stable period: 09 October-27 February 2014. Number of observations is 363.
Crisis period: 28 February 2014- 03 March 2015. Number of observations is 263.
To determine optimal number of lags in both VAR systems SBIC information criterion was used. This information criterion suggested using 2 lags for both VAR models.
With bold we indicated that during the stable period the null hypothesis of no cointegrating vectors between our variables can be rejected at 10% significance level, while the null hypothesis of no cointegration cannot be rejected during the crisis period.

**Appendix P** – Annualized daily volatility: Granger causality test results, 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 | 6.4930 | 0.000 | S&P 500 ↔STOXX Europe 50***(*) |
| STOXX Europe 50 does not Granger cause S&P 500 | -1.7763 | 0.077 | |
| S&P 500 does not Granger Cause RTS | 4.8460 | 0.000 | S&P→ RTS*** |
| RTS does not Granger Cause S&P 500 | 1.5459 | 0.123 | |
| STOXX Europe 50 does not Granger cause RTS | -1.8540 | 0.065 | STOXX→ RTS* |
| RTS does not cause STOXX Europe 50 | 1.4440 | 0.150 | |
| **Panel B. Crisis Period** | | | |
| Null-hypothesis: | F-statistic | Prob | Conclusion |
| S&P 500 does not cause STOXX Europe 50 | 15.9041 | 0.000 | S&P 500 →STOXX Europe 50*** |
| STOXX Europe 50 does not Granger cause S&P 500 | 0.6278 | 0.429 | |
| S&P 500 does not Granger Cause RTS | 6.6514 | 0.011 | S&P→ RTS** |
| RTS does not Granger Cause S&P 500 | 0.2004 | 0.658 | |
| STOXX Europe 50 does not Granger cause RTS | 4.1175 | 0.044 | STOXX→ RTS** |
| RTS does not Granger cause STOXX Europe 50 | 0.9151 | 0.340 | |

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

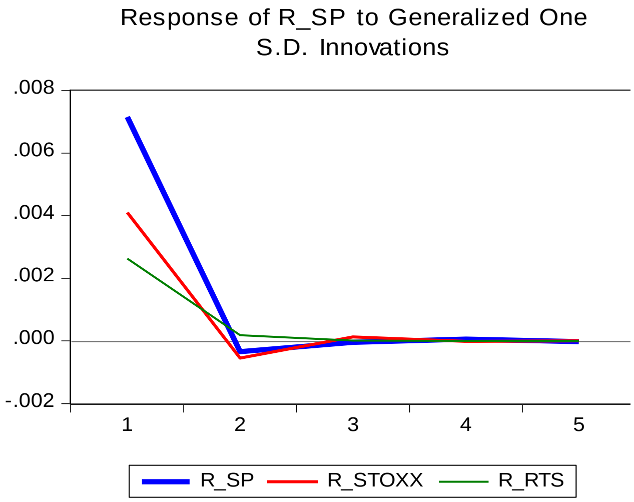
Stable period: 09 October-27 February 2014. Number of observations is 363.

Crisis period: 28 February 2014- 03 March 2015. Number of observations is 263.

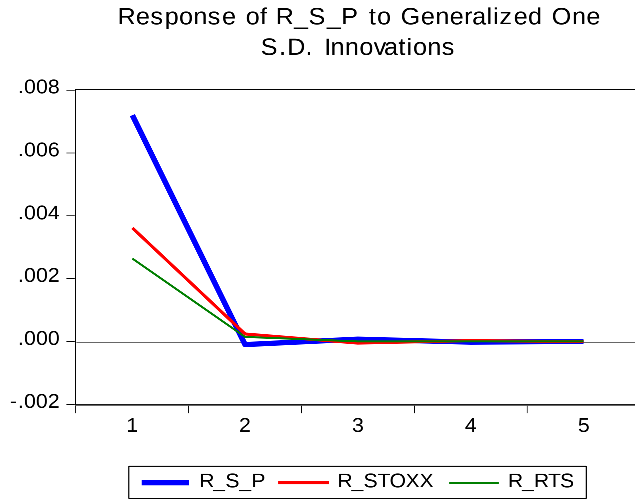
To determine optimal number of lags in the VAR system (for the crisis period) SBIC information criterion was used. Lag length was determined to be 1. Similarly, the lag length of the VECM model was assigned as 1.

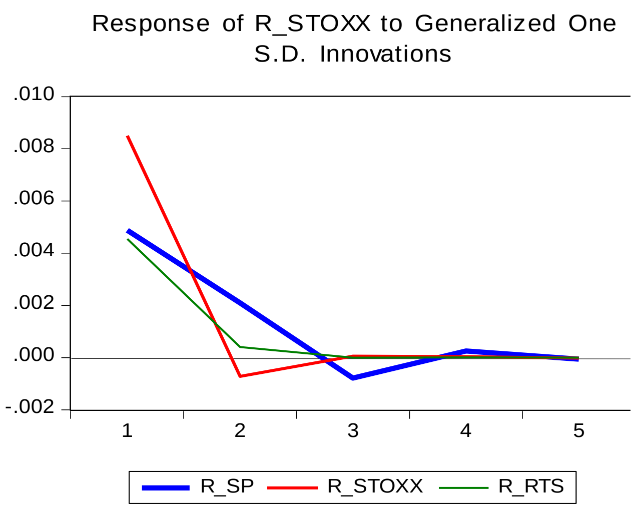
**Appendix Q** –Annualized daily volatility: Generalized impulse response function results, made by the authors using data from *Thomson Reuters Datastream*

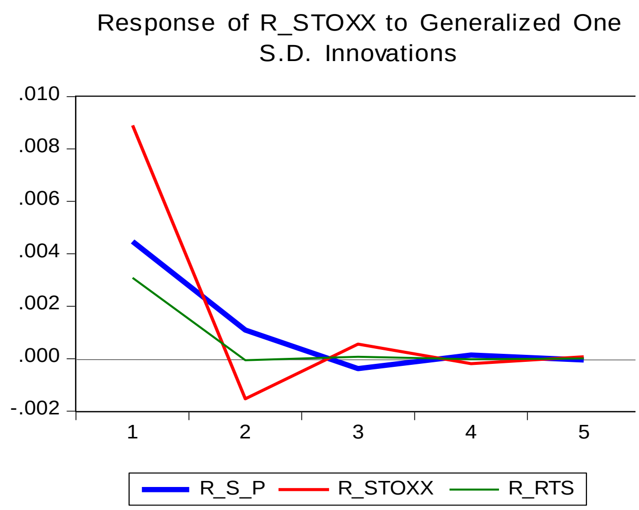
Stable period,

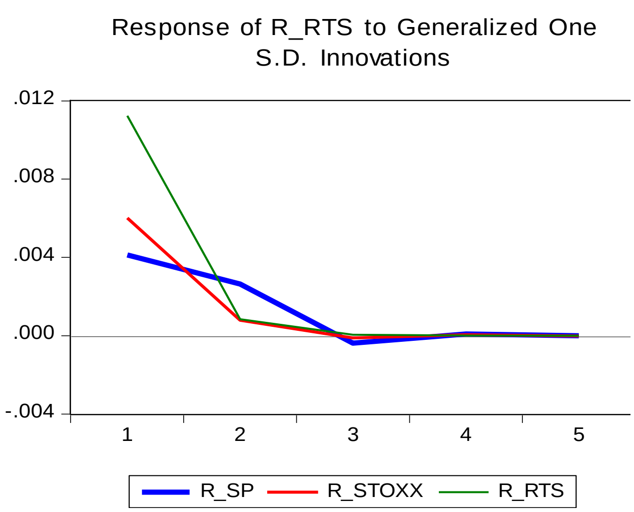


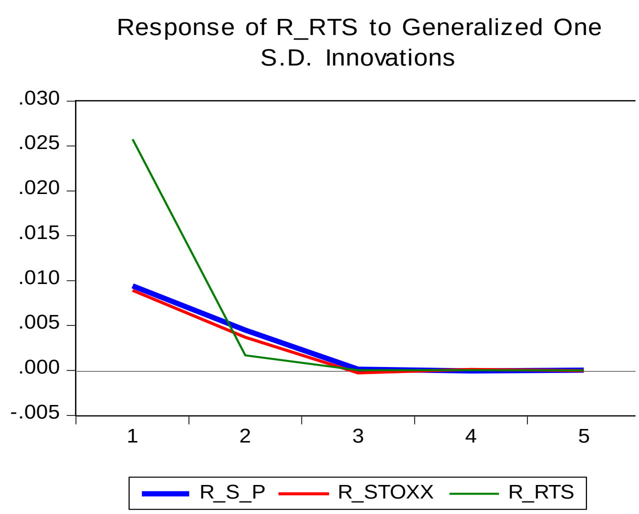

Crisis period



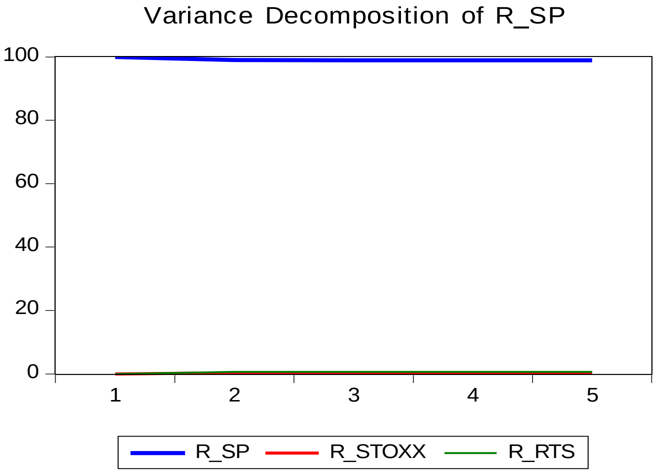



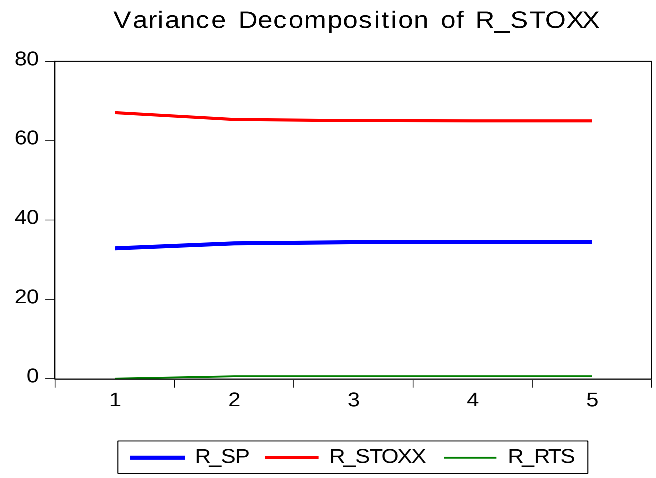



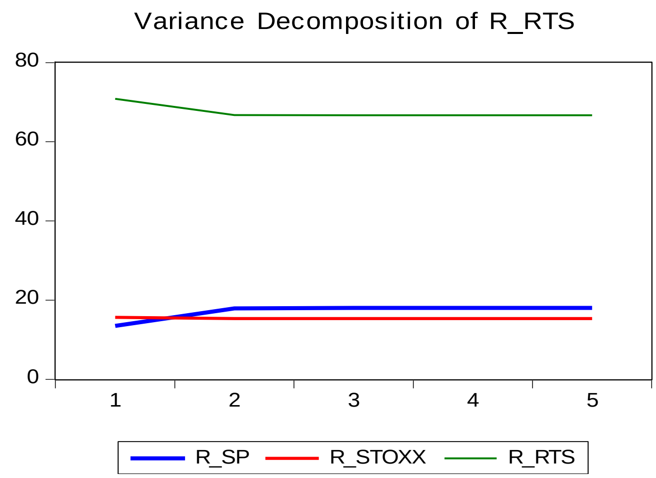



**Appendix R** –Annualized daily volatility: Variance decomposition, made by the authors using data from *Thomson Reuters Datastream.*

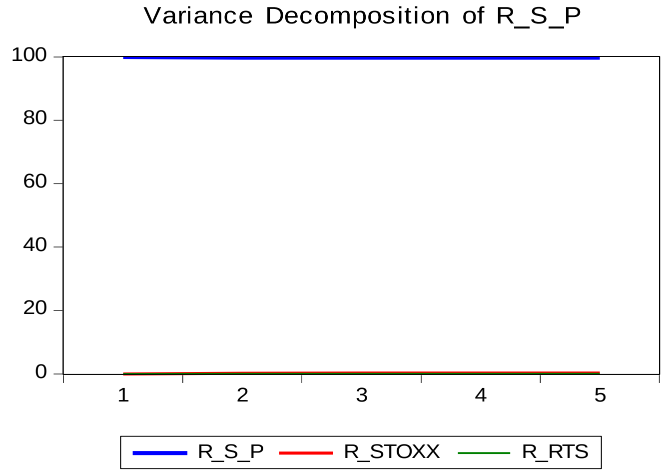
**Stable period**

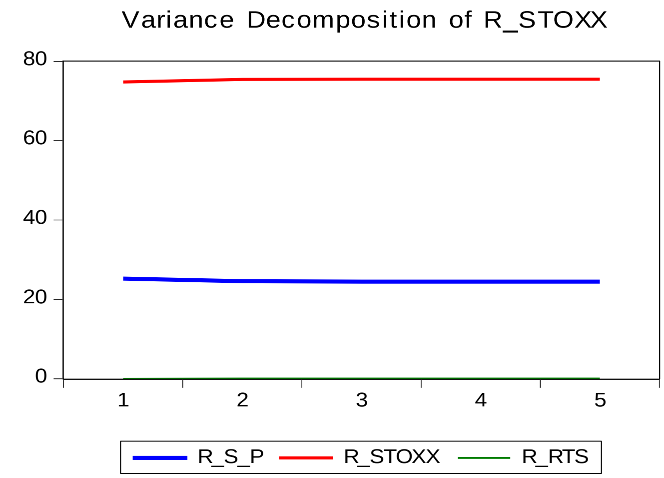


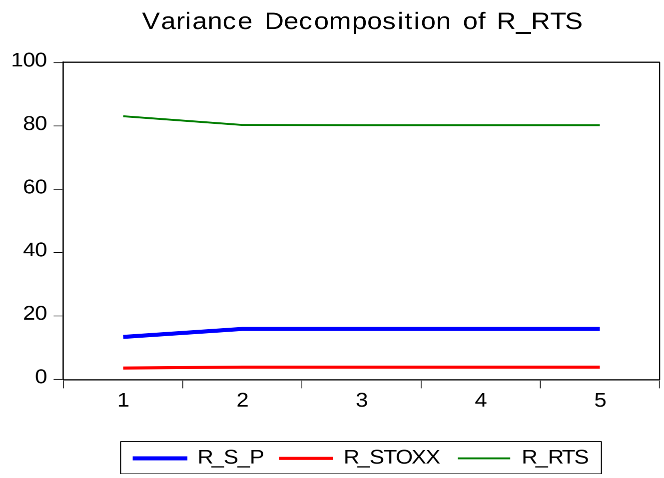




**Crisis period**



**Appendix S** –Annualized daily volatility: GARCH-BEKK model results, made by the authors using data from *Thomson Reuters Datastream*

| **A. Stable Period** | | | | | | |
|---|---|---|---|---|---|---|
| | Coefficient | Standard error | Coefficient | Standard error | Coefficient | Standard error |
| | $U.S. (i = 1)$ | | $EU\ (i = 2)$ | | $Russia\ (i = 3)$ | |
| $b(i, 1)$ | 0.005657*** | 0.0004889 | - | - | - | - |
| $b(i, 2)$ | 0.004735*** | 0.0014088 | 0.00657*** | 0.000463 | - | - |
| $b(i, 3)$ | 0.004847* | 0.0029305 | 0.00434*** | 0.001005 | 0.00926* | 0.001100 |
| $c(i, 1)$ | -0.13097 | 0.1200374 | 0.07705 | 0.104520 | 0.16783** | 0.071771 |
| $c(i, 2)$ | 0.01139 | 0.1134713 | -0.47575*** | 0.138533 | 0.20579** | 0.092055 |
| $c(i, 3)$ | -0.17569 | 0.1438330 | -0.18499 | 0.162562 | 0.01252 | 0.120930 |
| $g(i, 1)$ | 0.09691 | 0.4356682 | -0.07645 | 0.269883 | -0.03109 | 0.088185 |
| $g(i, 2)$ | 0.06884 | 0.2873660 | -0.05206 | 0.160712 | -0.19999 | 0.197064 |
| $g(i, 3)$ | 0.02811 | 0.1755002 | -0.01590 | 0.100532 | -0.04444 | 0.289879 |
| **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*** | 0.0013281 | - | - | - | - |
| $b(i, 2)$ | 0.00098 | 0.0039337 | 0.00179 | 0.1138046 | - | - |
| $b(i, 3)$ | 0.00048 | 0.0030651 | 0.00017 | 0.1915214 | -0.01793 | 0.027825 |
| $c(i, 1)$ | -0.03373 | 0.1328985 | 0.17204** | 0.0799761 | 0.05629** | 0.027825 |
| $c(i, 2)$ | -0.57905*** | 0.1106722 | 0.37697*** | 0.1138046 | 0.09050** | 0.036996 |
| $c(i, 3)$ | 0.71332 | 0.4631689 | 0.08572 | 0.1915214 | 0.37025*** | 0.078450 |
| $g(i, 1)$ | -0.08545 | 0.2779901 | 0.16781 | 0.1780937 | -0.17135 | 0.113665 |
| $g(i, 2)$ | -0.18427 | 0.6485509 | 0.33294 | 0.5010435 | -0.36097*** | 0.098831 |
| $g(i, 3)$ | -0.22277 | 1.0033212 | 0.42252 | 0.9477419 | -0.43915** | 0.220674 |

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