Title: IS THE GLOBAL FINANCIAL STABILITY THREATENED IN CASE A NEW RUSSIAN VIRUS BURSTS?

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Abstract: There is an old financial press sentence saying that when the US sneezes the world catches cold. But is it true for Russia? The world still remembers the “Russian Virus” from 1998 and its extensive spillover effects. Currently, with the beginning of the Crimean crisis and the subsequent US and EU strictures imposed on Russia, the question on the world financial stability is again up to date. The rounds of sanctions led to deprecation of the rouble, downgrade of the Russian sovereign rating, flight of capital and stock market downturn. But what is going to happen with the world financial markets if a new Russian Virus occurs? The goal of the current paper is to provide an in-depth analysis in lines with this question. For this purpose a wavelet-based method is employed due to its powerful analytical properties which are especially well-suited to the analysis of stock market data. In particular the chosen method reveals information on linkages that remain hidden when utilizing conventional econometric apparatus and identifies precisely structural breaks.

Key words: Russian stock market, Crimean crisis, stock market integration, wavelet transform

JEL: F30, F36, G15
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I. Introduction

The Russian stock market was reestablished in the mid-1990s after the transition from planned to market-driven economy. During this period the country went through severe recession, deprecation of local currency and default on sovereign debt ending up into “the Russian Virus”, which spread globally, shaking both emerging and developed markets and causing the famous near-collapse of the American LTCM. Nine years later, the market has already revived reaching record high levels of market size and liquidity with its peak in 2007 when the Russian stock market was amongst the top ten stock exchanges in terms of its market-cap value. However, the burst of the mortgage bubble and the subsequent credit crisis led to market collapses all over the globe, including Russia, but unlike most of the East European countries, the Russian stock market was characterized by a subsequent growth, which lasted until the middle of 2011 when the economic slowdown in the Eurozone led to decrease in stock market prices. Yet, in the subsequent period the Russian stock market remained relatively stable just until recently.

The Russian intervention in Ukraine and the aftermath establishment of Crimea and Sevastopol as subjects of the Russian Federation were followed by a sequence of US and EU rounds of sanctions, which resulted into depreciation of the ruble, downgrading of sovereign rating and a significant flight of capital. In particular, the strictures led to a considerable selloff and subsequent downfall of the Russian stock market. Even though signs of recovery were noted during the last months, it is still questionable for how long the stock market and the ruble could sustain to the sanctions’ tension. In order to offset the ruble depreciation the Central Bank of Russia has raised several times its key interest rate and sold reserves amounting to 22,296.84 millions of USD\(^1\) only for the month of March 2014.

Furthermore, the third round of EU sanctions\(^2\), also referred to as “tier three”, imposed restrictions on five state-controlled Russian banks’ ability to borrow money in EU financial markets. Among them are Sberbank and VTB Bank whose cumulative weight representation in the Russian benchmark indices is nearly 18%. The sanctions also introduce arms embargo and restrict the export of technology connected with deep water, Arctic and shale oil extraction. Those measures put in the context of approximately 50% total weight of oil and gas companies constituting the Russian benchmark indices cast serious doubts on the Russian stock market future performance.

All these facts together with the financial press qualifying the current situation with the Russian economy as “on the verge of recession”\(^3\) inevitably wake up memories on the 1998 Russian crisis provoking fears for the future financial stability of the world. Even though more than 15 years have passed since the Russian Virus spread, its huge impact on the global finances is evidenced by the presence of significant body of contemporary research engaged with it. As argued by Dungey and co-authors (Dungey, et al., 2006) while the influence of the Mexican and the Asian crisis was limited to other emerging markets and regions, the Russian crisis influenced both the developed and emerging economies. According Saleem (Saleem, 2009), “Russia’s 1998 financial crisis increased volatility in global security markets with surprisingly severe and widespread contagion”. In (Kali & Reyes, 2010) this extensive spillover effect is explained through a network model based on

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2. The US, Australian and Norwegian authorities followed similar lines of sanctions against Russia.
the existing trade relationships, which implies that the crisis was channeled to the developed economies due to presence of strong market interrelations. Furthermore, as suggested in recent research papers\textsuperscript{4}, economic and financial integration is a major driver of a crisis’ spillover.

All these findings raise the question on how strong is the integration of the Russian stock market to the leading world financial markets. Put it differently, could the strictures imposed by the USA and the EU on Russia eventually end up into domino effect causing stock market crashes worldwide? The goal of the current paper is to provide the answer of this question. On one hand, it would enhance the view on the economic side of the undertaken political measures and their probable consequences. On the other hand, the importance of carrying out an in-depth analysis is determined by the turbulences characterizing the US and the EU equity markets during the last few years. Hence, it is further investigated if since the beginning of the Crimean crisis there are already indications of contagion and conclusions on presence of spillover tendencies are drawn.

The paper objective is accomplished within the following task framework. As a first step, the theoretical grounds of the study are laid down in the context of an extensive literature review on crises’ transmission mechanisms, which serves as a basis to define a methodology, enabling measurement of integration and detection of contagion. The next task comes down to data collection, application of the described methodology, and presentation of major results. In order to deliver proper interpretation of results, a brief discussion on the Russian stock market specifics is provided. Finally, a discussion highlighting spillover prospects is carried out. It should be emphasized that wavelet coherency is chosen as a research tool as it provides a natural platform to analyze stock market linkages. At the same time, it uncovers information that might be missed when conventional econometric tools are engaged.

Rest of the text is structured as follows. Section II outlines the theoretical framework of the study. The adopted research methodology is described in Section III. Section IV presents the dataset as well as the obtained results, followed by a discussion. Section V concludes.

### II. Literature review: Interdependence and contagion

In order to achieve the goal of the current research, it is crucial to outline carefully the channels through which a crisis in one market propagates to other markets. The economic intuition suggests that when two markets are well integrated through trade, investment and financial relationships, a crisis occurrence in one of them is likely to spread rapidly to the other. As noted by Tong and Wei (Tong & Wei, 2011), an exposure to financial globalization may carry increased vulnerability to a financial crisis. Several recent papers are supportive to this hypothesis. In the context of the global financial crisis of 2007-2009, Stiglitz (Stiglitz, 2010) carries out an investigation on the optimal degree of financial integration. The author explains the issue with the high degree of financial integration through a comparison with an integrated electrical grid, where failure in one part of the system can lead to system-wide failure. Mendoza and Quadrini (Mendoza & Quadrini, 2010) also study the US mortgage bubble spillover. An important finding is that with globalized markets, country-specific shocks propagate to other economies including a worldwide drop in asset prices. Furthermore, according to the research of Kali and Reyes (Kali & Reyes, 2010) crisis’ effects are amplified if the epicenter country is better integrated into the trade network.

\textsuperscript{4} A detail review on the most important papers is performed in Section II.
Brière and co-authors (Brière, et al., 2012) distinguish between globalization and contagion in their extensive study on the transmission of numerous crises during the period 1978-2010. A major conclusion is that economic globalization together with growing integration of financial markets is the main reason for the observed correlation increases and contagion on equity markets appears as an artifact. However, as pointed out by the authors, it is econometrically difficult to separate contagion from globalization. This finding poses the question what is the difference between globalization (integration) and contagion, and why it is important to distinguish between them.

The most popular and widely used definition of contagion is introduced by Forbes and Rigobon (Forbes & Rigobon, 2002). They define contagion as a significant increase in cross-market linkages after a shock and point out that if two stock markets exhibit high level of co-movement during calm periods, then the continued high correlation after a shock to one of the markets suggests interdependence, while contagion is present only in the case of a significant co-movement increase. Bekaert and co-authors (Bekaert, et al., 2014) apply this definition with a slight modification. They refer to co-movements, greater than those implied by market fundamentals, as contagion. Such a formulation is appealing from analytical point of view, as it provides the opportunity to differentiate between expected and unexpected spillover effects.

Summing up, interdependence, i.e. high degree of economic and financial integration, is a major channel though which crises propagate. However, often the severity of a spillover to other economies is greater than that implied by market fundamentals. In this case, the unexpected spillover is regarded as contagion. The sources of contagion might be either rational or irrational. Ciprini and Guarino (Cipriani & Guarino, 2008) illustrate how herd or contrarian behavior can lead to financial contagion. Under herd behavior is meant the case when all traders choose the same action irrespective of the available information and contrarian behavior refers to the situation when informed traders act against the market. However, contagion can also be caused by rational investors’ decisions. On one hand, during crisis investors might face needs to raise liquidity. For example, the role of selling pressure in the transmission of the 2007-2009 financial crisis is documented by Calomiris and co-authors (Calomiris, et al., 2012). Another source of rational contagion is the so-called wake-up call (see for example (Giordano, et al., 2013)), when the crisis originally restricted to one country prompts investors to reassess the risk of other countries.

The understanding for contagion of Bekaert and co-authors (Bekaert, et al., 2014) is adopted in the current paper. The analysis is carried out in two steps. On one hand, the degree of the Russian stock market integration to the US and major EU equity markets is investigated. Based on the delivered results perspectives for expected spillover (i.e. spillover implied by market fundamentals) are outlined. On the other hand, soon after the beginning of the Crimean crisis, the Russian stock market has registered significant price drops. Therefore, it is further analyzed if signs of contagion are already present.

The estimation of the spillover effects, implied by market fundamentals, is not an easy task when conventional econometric tools are engaged. Bekaert and co-authors (Bekaert, et al., 2014) perform such an estimation employing a three-factor model framework. The authors use the model as a benchmark of what the market fundamentals imply. If the model under-predicts the actual correlations, than the authors conclude on presence of contagion. Even though this approach provides the opportunity of a detailed analysis and in particular, it enables identification of different channels of contagion, its major drawback is the necessity to carry out specification, estimation and selection procedures based on a number of
assumptions and requiring significant data availability on numerous financial and macroeconomic variables.

In order to identify changes in international correlation matrices, which took place after some crisis occurrence, Brière and co-authors (Brière, et al., 2012) apply a generalized version of the Jennrich test over normal and crisis periods. A major difficulty in such type of analysis is the assessment of crises’ start and end dates. (Kim & Kim, May 11, 2010) estimate dynamic conditional correlations across countries through multivariate GARCH models (often referred to DCC-GARCH model). They analyze spillover effects of the US financial crisis to five emerging Asian countries. Significant advantage of this approach is that it does not require knowledge on the exact date when contagion occurred. However, results are sensitive on the model specification and underlying assumptions.

Other approaches employing analysis at micro (Calomiris, et al., 2012) and macro [ (Rose & Spiegel, 2010) (Rose & Spiegel, 2012) ] level are available in the literature. In the current paper, an approach based on wavelet coherency analysis is adopted as it is characterized by several important advantages. First of all the approach does not rely on any underlying assumptions, which assures the robustness of the delivered results. Secondly, it is extremely parsimonious in terms of data requirements. Last, but not least, the wavelet coherency provides a natural platform for the analysis of stock market integration and contagion. Similarly to the DCC-GARCH framework, it does not require any knowledge on the exact start and end date of a crisis, but at the same time no underlying model is assumed.

III. Methodology

Wavelet coherency is a method based on the wavelet transform, and it is utilized for detection of co-movements between two time series in the time-frequency plane. The wavelet transform is known to be a generally well-suited tool to the analysis of the complicated structure of financial data. As explained by Ramsey (Ramsey, 1999), financial data is the output of decisions and actions taken by numerous economic agents operating simultaneously over different investment horizons. For example, a pension fund manager acts over an investment horizon of at least several years, while the speculator trades on a daily, hourly or even on a minute basis. This means that a given financial time series might be viewed as a mixture of different frequency ingredients. On the other hand, the wavelet transform provides the opportunity to break down this complicated structure into simpler components, each of them characterized by a specific frequency. This property enables multiscale analysis and reveals hidden information5.

On the other hand, even though the wavelet coherency is still quite fresh application in the field of empirical finance, it has already proven to be a powerful analytical tool. Rua and Nunes (Rua & Nunes, 2009) are probably the first to apply the wavelet coherency in the analysis of stock market co-movements. The authors present the linkages that exist between the major developed markets at different frequencies where each frequency is related to a particular investment horizon. This representation provides the analyst with information that is otherwise not that obvious. A major step in the development of the wavelet coherency financial applications is done by Vacha and Barunik (Vacha & Barunik, 2012). The authors illustrate empirically the equivalence between the sum of the wavelet coherency coefficients in a given time point and the Engle’s dynamic conditional correlation coefficient (Engle, 2002), emphasizing on the fact that while the estimation of the latter involves assumptions-

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5 The interested reader is referred to (Gençay, et al., 2001), (Ramsey, 2002) and (In & Kim, 2013) for an extensive review on the benefits of using wavelets for analysis of financial time series.
based model, the estimation of the former is done regardless of the nature of the underlying process.

Furthermore, wavelet coherency provides the researcher with a detailed breakdown of the existing relationships into different frequency components, thus enhancing deeper analysis. Ranta (Ranta, 2013) utilizes this fact to propose a novel way for analyzing presence of contagion. Its major advantage is that while the identification of contagion through the classical correlation method is found to raise biased results (Forbes & Rigobon, 2002), the proposed application avoids this issue. In line with the Ranta’s approach Bogdanova (Bogdanova, 2014) utilizes wavelet coherency in order to investigate the dynamics of the Greek stock market integration with the world financial markets. It is demonstrated that this method enables precise identification of structural changes in stock market linkages that could not be captured with the conventional econometric tools. A major finding is the occurrence of structural break in the stock market linkages with the beginning of the Greek sovereign debt crisis. In sum, all these papers illustrate the strong analytical potential of the wavelet coherency and justify its application in the analysis of crisis spillover effects. Before presenting the analytical framework, it is necessary to provide a brief introduction in the wavelet transform and wavelet coherency. The exhibition in section III.1. follows the presentation in (Aguirar-Conrara & Soares, 2014).

III.1. Brief introduction in wavelet transform and wavelet coherency

A function $\psi(t) \in L^2(\mathbb{R})$ is said to be a mother wavelet if it satisfies the so called “admissibility condition” which is a decay condition and ensures that the function is well localized both in time and frequency. For functions with sufficient decay the admissibility condition is equivalent to requiring that

$$\Psi(0) = \int_{-\infty}^{\infty} \psi(t) dt = 0,$$

where $L^2(\mathbb{R})$ denotes the set of square integrable functions and $\Psi(\omega)$ denotes the Fourier transform of $\psi(t)$. A family of wavelet daughters $\{\psi_{s,\tau}; s, \tau \in \mathbb{R}, s \neq 0\}$ can be obtained by scaling and translating the mother wavelet $\psi$:

$$\psi_{s,\tau} = \frac{1}{\sqrt{|s|}} \psi\left(\frac{t-\tau}{s}\right),$$

where $s$ is a scaling factor controlling for the width of the wavelet and $\tau$ is a translation parameter controlling its location. Given a time series $x(t) \in L^2(\mathbb{R})$ its continuous wavelet transform with respect to the wavelet $\psi$ is defined as follows:

$$W_{x;\psi}(\tau, s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|s|}} \psi^*\left(\frac{t-\tau}{s}\right) dt,$$

where the asterisk denotes complex conjugate. For simplicity of notation the wavelet transform $W_{x;\psi}(\tau, s)$ will be denoted by $W_x$ in the text that follows. The cross-wavelet transform of two time series, $x(t)$ and $y(t)$, is given by Eq. (4):

$$W_{xy} = W_x W_y^*.$$

For the purpose of measuring co-movement it is suitable to utilize complex-valued wavelet and the most common choice is the Morlet wavelet which is utilized in the current paper as well. The wavelet coherency of the time series $x(t)$ and $y(t)$ is denoted by $R_{xy}$ and is defined by Eq. (5):
\[ R_{xy} = \frac{|s(w_{xy})|}{\sqrt{s[(w_{xy})^2]}}^{1/2}, \]  

(5)

where \( S \) is a smoothing operator in both time and scale and \( 0 \leq R_{xy} \leq 1 \). The closer the value of \( R_{xy} \) to 1, the stronger is the degree of synchronization between the time series \( x(t) \) and \( y(t) \), i.e. they are exhibiting stronger co-movement.

In order to describe the procedure for identification of interdependence and contagion, it is necessary first to provide some explanations on the output of Eq. (5). At Figure 1 is presented the wavelet coherency between the weekly return series of the stock indices RTS and S&P 500. The numerical realization of Eq. (5) is performed through a freely available Matlab toolbox associated with the theoretical framework presented in the paper of Aguiar-Conraria and Soares (Aguirar-Conrara & Soares, 2014). The toolbox is available at http://sites.google.com/site/aguiarconraria/joanasoares-wavelets.

Figure 1: Wavelet coherency of the return series of RTS Index and S&P 500. 9, 14

As might be seen from the figure, the results are presented in the form of a color map, due to the fact that wavelet coherency provides three-dimensional description: each pixel of the map corresponds to a particular value of \( R_{xy} \) \( (0 \leq R_{xy} \leq 1) \) at a specific point in the time-frequency plane. The x-axis corresponds to the time scale and the y-axis – to the frequency scale. Similarly to a geography map, each value of \( R_{xy} \) is denoted by color. The utilized color code is presented next to the map. In order to ease interpretation of results, the utilized frequencies are converted into time units, where the finest scale corresponds to one week, and the coarser scale – to five years. Additionally, the statistically significant
coherencies are determined on the basis of Monte Carlo experiments\(^6\) and then they are contoured on the map. The cone of influence is plotted with tick black line and it represents the region in which the transform suffers from edge effects.

**III.2. Wavelet-based methodology for identification of interdependence and contagion**

The proposed application is built on three recent papers. The research of Ranta (Ranta, 2013) forms the core of the suggested procedure. As already mentioned, he proposes a new way of measuring contagion, which is robust to the critique of Forbes and Rigobon (Forbes & Rigobon, 2002). Ranta’s approach states that when the low frequency coherency exhibits stable behavior but at the same time there is an increase in the coherency corresponding to the higher frequencies, this is indicative for presence of contagion. This idea is combined with the findings of Bogdonova (Богданова, 2014) and Vacha and Barunik (Vacha & Barunik, 2012) in order to develop a clear procedure for identification of interdependence and contagion.

In the spirit of the work of Ranta (Ranta, 2013), a distinction between co-movements at different frequencies is used. However, instead of analyzing just lower and higher frequency co-movements, the frequency axis is portioned into high, medium, and low frequency bands. In this way the observed co-movements are categorized into short-term, mid-term, and long-term co-movements. In order to proceed further, this idea is linked to the results presented at Figure 1. It might be seen that the wavelet coherency coefficients are calculated over frequencies ranging from 1 week to 5 years. To be particular, conclusions on the short-term co-movements are drawn from values of the wavelet coherency coefficients, corresponding to the highest frequencies. In the current paper, the highest frequency band is considered to span from 1 week to 3 months\(^7\). These co-movements might be interpreted as follows. By definition, the highest frequencies are associated with the noise contained in the analyzed data, which essentially represents the random component in a given time series. This random component in turn is driven by the news. Therefore, if two markets are affected by the same news, than co-movements at the highest frequencies would be observed in calm as well as during crisis periods.

The long-term co-movements are determined from the coefficients in the low frequency band. As low will be considered the frequencies above 1 year\(^8\). For the interpretation of the low frequency coefficients is employed the paper of Bogdanova (Богданова, 2014). A major conclusion is that information on the extent to which two stock markets are integrated could be easily obtained through inspection of the wavelet coherency coefficients corresponding to the low-frequencies bands. The intuition behind this idea is that these frequency co-movements reflect the existence of long-term relationships, which are attributed to the presence of significant integration. Consequently, co-movements detected at the low frequencies are driven by the market fundaments and could be used to draw conclusions on interdependence.

The information contained in the medium frequency bands (3 months – 1 year) can be used to infer on presence of contagion. As already explained, contagion is considered generally to be a co-movement (or correlation) that is in excess to what is implied by market

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\(^6\) For additional details the reader is referred to (Aguirar-Conrara & Soares, 2014).

\(^7\) The economic intuition behind this choice is that generally deposits and bonds, whose maturity is 90 days or less, are considered as the most liquid assets.

\(^8\) This choice is determined on the fact that often in Economics periods greater than 1 year are referred to as long-term periods. For example, in the accounting of assets, the border-line between long-term and short-term assets is 1 year.
fundamentals, i.e. the co-movement in excess to that caused by stock market integration. As the low frequencies reflect the co-movement caused by market integration (i.e. the co-movement caused by the presence of fundamental relationships), than areas of significant coefficients corresponding to the medium frequencies are indicative of contagion. This idea might be motivated as follows. Vacha and Barunik (Vacha & Barunik, 2012) carried out an analogue between the averaged wavelet coherence coefficients (the statistically insignificant coefficients are considered to be zero when averaging) at given time point and the respective conditional correlation coefficient\(^9\) (see (Engle, 2002)). As soon as such a parallel is possible, one could intuitively conclude on the fact that significant coefficients at the medium frequencies will contribute to increased averaged values, i.e. the overall co-movement will be in excess to the co-movement caused solely by the market fundamentals. On the other hand, as already mentioned, the highest frequency co-movements should be present (or absent) both in calm and in turmoil periods as soon as the same news influence both of the markets. A visual summary of the outlined procedure is provided with Figure 2.

![Wavelet-based methodology for identification of integration (interdependence) and contagion.](image)

**Figure 2:** Wavelet-based methodology for identification of integration (interdependence) and contagion.

### IV. Empirical analysis

The goal of the current paper is to answer the question of what is going to happen with the world financial markets if the US and EU sanctions cause the Russian stock market to collapse. In order to answer to this question, a detailed data analysis is carried out, following the methodology, outlined in Section III. For this purpose pairwise wavelet coherencies are calculated for time series representing the Russian and the major world equity markets. In particular, the focus is set on the EU and US stock markets as they went through a series of turbulent periods since the beginning of the US mortgage crisis. The

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\(^9\) The conditional correlation coefficient is estimated within ARMA-GARCH framework, therefore, it is adjusted for the increase in the volatility during crisis. This means that the conditional correlation might be a useful tool when examining contagion. However, the robustness and unbiasedness of the delivered results is conditional upon the model specification.
sample of EU stock markets consists of the stock markets of Germany, the UK, France, and Italy. The dataset comprises price observations on the major stock indices of the investigated markets.

IV. 1. Data

The raw data consists of the closing prices of the stock indices enlisted in Table 1 of Appendix A. Figure 7 in Appendix A provides visual data representation. The sample period spans from 1-Jan-2004 to 4-Aug-2014. It should be noted that a weekly sampling rate is applied in order to avoid the issue with different working hours and official holidays of the investigated stock exchanges. Stock prices are known to exhibit first-order nonstationarity and their empirical distributions are usually asymmetric. That is why a routine transform into log-returns is advisable as it deals with the issue of nonstationarity and reduces skewness. If \( \{P_t, t = 1, 2, \ldots, T\} \) denotes a time series of price records on a given asset, than the calculation of the respective log-returns \( \{R_t, t = 2, 3, \ldots, T\} \) is derived through Eq. (6):

\[
R_t = \ln \frac{P_t}{P_{t-1}}, \quad t = 2, 3, \ldots, T.
\]  

Thus, the closing prices of the investigated stock market indices are converted into weekly log-returns through application of Eq. (6). Table 2 of Appendix A presents the descriptive statistics of the log-returns. The augmented Dickey-Fuller test confirms stationarity of all of the return series. It might be noted that the RTS returns are characterized by higher volatility as compared to the rest of the indices. Also, all the series exhibit leptokurtosis, which is a common feature for financial data.

IV.2. Results

![Wavelet coherence of the return series of RTS Index and DAX](image)

**Figure 3: Wavelet coherency of the return series of RTS Index and DAX.**
Figure 4: Wavelet coherency of the return series of RTS Index and FTSE 100. 17

Figure 5: Wavelet coherency of the return series of RTS Index and CAC 40. 17
Using the log-returns described in section IV.1, pairwise wavelet coherencies are calculated, following Eq. (5). As already mentioned, the numerical realization is executed through a freely available Matlab toolbox associated with the theoretical framework presented in the paper of (Aguirar-Conrrara & Soares, 2014). The wavelet coherency between RTS and S&P 500 returns is presented at Figure 1. Figure 3, Figure 4, Figure 5, and Figure 6, provide the respective coherencies between RTS and rest of the investigated indices. Before moving on with the results interpretation, it would be helpful to provide a brief overview on the Russian stock market development and specifics.

IV.3. Discussion

IV.3.1. Some important characteristics of the Russian stock market

The Russian stock market was reestablished in 1996 after the transition from centralized to market-driven economy. While large equity market size is typical for transition countries due to the privatization process, it should be noted that the Russian stock market capitalization was catching up the country’s GDP growth until the beginning of the 2007-2009 financial crisis. Data on market cap and liquidity indicators is provided in Table 3 of Appendix B. As might be seen in 2005 and 2006, the market-cap value has almost doubled as compared to the previous year’s value. This growth is explained with the significant increase in the IPOs during that time. According to a research of Deutsche Bank\textsuperscript{10}, from the revival of the Russian stock market until the end of 2004 only 18 IPOs have taken place. On the other

\textsuperscript{10} The research is available at http://www.dbresearch.com/PROD/DBRINTERNET_EN-PROD/PROD0000000000214153/Russia's+financial+sector%3A+Financial+deepening+will+support+long-term+growth.PDF.
hand, an overview of the Russian IPOs for the period 2005 – 2013, carried out by PwC\textsuperscript{11}, reports altogether 14 IPOs in 2005, 11 of which took place at the London Stock Exchange (LSE) and 3 at the Moscow Exchange (ME). The corresponding figures for 2006 and 2007 are 28 IPOs (19 of them at the LSE, 7 at the ME, 1 at NASDAQ, and 1 at Deutsche Börse), and 32 IPOs (15 of them at the LSE, 14 at the ME, 2 at NASDAQ, and 1 at Deutsche Börse) respectively.

Therefore, since 2005 it might be expected an increased integration of the Russian stock market with the leading world markets. Furthermore, as pointed out by Beakert and co-authors (Bekaert, et al., 2002), the increased stock market integration is associated with an increase in the market size and liquidity. Along with the growth in the stock market capitalization, the figures, presented in Table 3 of Appendix B, show an improving level of liquidity since 2005, which additionally reinforces the expectations on increased integration of the Russian market since 2005.

Apart from the size and liquidity, it is important to pay attention on the industry loads of the Russian equity market. This might be easily done through an inspection of the structure of the benchmark indices RTS and MICEX\textsuperscript{12}. Both of them are calculated based on the prices of the 50 most liquid stocks of Russian issuers, representing main sectors of the Russian economy. Figure 8 from Appendix B presents the cumulative weights of the benchmark indices constituents, calculated by industries. It might be seen that the Oil&Gas industry cumulative weigh amounts to approximately 50%. The next largest share falls on the Banking sector with cumulative weight of almost 18%, followed by Metals&Mining and Telecommunications.

A handy summary, which should be taken into account when interpreting results, is that the Russian stock market is heavily represented by the Oil&Gas industry. Another important fact is that since 2005 the market opens through a sequence of IPOs, with considerable amount of listings at LSE.

\textbf{IV.3.2. Russian – US stock market co-movements}

The co-movements between the Russian and the US stock markets, presented at Figure 1, are interpreted following the methodology described in Section III.2.

\textit{Co-movements in the highest frequency band (1 week – 3 months)}

As already explained, the highest frequencies, by definition, contain the noise, which is considered to be driven by the news. Hence, the areas of statistically significant coefficients corresponding to these frequencies represent returns’ co-movements caused by news on common factors influencing both of the markets. It is not surprising to find that throughout the investigated period numerous areas of statistically significant coefficients are present. However, an interesting finding is that since the beginning of 2014 no areas of significant values are observed for the frequency bands beyond 1 month. \textit{This means that different news affect the recent stock market movements of the US and Russia}, which is a logical finding in the light of the geopolitical events, which have been taking place since the beginning of the year.

\textsuperscript{11} The paper is available at http://www.pwc.ru/en_RU/ru/capital-markets/publications/assets/a4_brochure_ipos_eng_print.pdf.

\textsuperscript{12} Both of the indices constituents are the same, but MICEX is denominated in rubles and RTS in dollars.
Co-movements in the lower frequency band (above 1 year)

According to the methodology, significant co-movements corresponding to the frequencies beyond 1 year, indicate integration of the investigated stock markets. It might be noted that until 2006 no significant coefficients are present. The only exception is the tight spot observed since the end of 2004. As it corresponds to the frequencies clustered around the 1 year line, it is arguable if the identified co-movement during this period represents contagion or it is an initial move towards integration. It should be noted that at that time important steps towards achievement of US-Russian cooperation in the fields of nuclear security and commercial energy were undertaken, as well as negotiations for the accession of Russia to the World Trade Organization (WTO) were carried out. Combining this information with the fact since 2005 the Russian stock market opens through a series of IPOs, leads to the conclusion that a shift towards stock market integration has taken place.

What is observed next for all of the frequencies above one year is a huge area of statistically significant coefficients, which spans until 2013. This implies significant integration of the American and the Russian stock markets during this period. However, it might be noted that only for the frequency band of 2.5 – 4 years the co-movement continues until 2013. For the other low frequency bands no statistically significant coefficients are present after the beginning of 2012. Therefore, it might be concluded that a process of segmentation has begun. The observed transition from integration to segmentation might be explained with the US energy boom, which has begun since 2012. The shale gas and tight oil production is changing the role of the US in the world energy market. While in 2005, the US is a major oil importer, nowadays it is considered to be approaching its dream of energy independence. Furthermore, according to the reference case forecast in the Annual Energy Outlook of EIA (U.S. Energy Information Administration, April 2014), from a net importer of 1.5 Tcf of natural gas in 2012 the United States is expected to become a net exporter even before 2020, with a net export amounting to 5.8 Tcf in 2040 (see the text at pp. MT-22 – MT-23).

Overall, what might be concluded from the low frequency band coefficients is that the US and Russian stock markets were considerably integrated until 2012 but in the aftermath period transition to segmentation is observed. This finding implies that a crisis in the Russian stock market is not likely to be propagated to the US stock market through the existing fundamentals.

Co-movements in the medium frequency band (3 months – 1 year)

Several important findings might be outlined. First of all, during the 2007 - 2009 financial crisis, an area of significant coefficients is observed at the frequency band of 6 – 12 months, which is indicative for considerable contagion. This means that the crisis influence on the Russian stock market was greater than that suggested by the existing trade, financial and investment relationships. Furthermore, from Sep-2008 to Mar-2009 significant co-movement is observed at the frequency band of 3 – 6 months, which reflects the severity with which the US stock market collapse has spread. The next instance of contagion is observed during 2010, at the 3 - 6 months frequencies. Overall, the US stock market was very volatile during this year. Several important events caused the registered stock prices falls, amongst them is the British Petroleum (BP) oil spill, which begun in the end of April and it took five

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13 It should be noted that only the results outside the cone of influence are analyzed, because the transform suffers from edge effects, hence the results inside it should be interpreted with special care.

14 The outlook is available at the following web address: http://www.eia.gov/forecasts/aeo/.
months to seal the oil leakage. This resulted into considerable fall in the stock prices of the multinational petroleum giant BP\(^{15}\). In the second half of 2011 again considerable co-movement between the US and the Russian stock returns is present at the medium frequency bands. This might be interpreted as a contagious effect of the US stock market decline in Aug-2011, caused by the S&P downgrade of US long-term sovereign credit rating.

The last area of significant coefficients at this frequency band spans from the beginning of 2012 until the early 2013. It should be noted that the American stock market performed pretty well in 2012, showing firm recovery from the 2009 record low levels. Indeed the identified co-movement cannot be interpreted as contagion, as according to the definition of Ranta (Ranta, 2013), in order to read such co-movements as contagion, the observed low frequency coefficients should be stable and this is not the case. As already commented a process of segmentation has begun in the beginning of 2012. Therefore, those coefficients might be interpreted as a transition from long- to short-term relationship between the two markets. An interesting finding is that no co-movements are observed after the beginning of 2013. This implies that the current downturn in the Russian stock market imposes no negative effects on the US stock market performance.

The analysis of the results, presented with Figure 1, is performed in a greater detail as thus is illustrated the ability of wavelet apparatus to extract information that is otherwise not that obvious. In particular, the utilized methodology allows to identify precisely transition from integration to segmentation and vice versa. It also detects accurately instances of contagion as well as structural breaks. As the wavelets’ analytical strength has already been demonstrated, in the text that follows similar analysis, but in a lesser detail is performed for the other pairs of wavelet coherencies, where the focus is set mainly on the co-movements associated with the recent geopolitical events.

**IV.3.3. Russian – German stock market co-movements**

The co-movements between the Russian and the German stock market are presented at [Figure 3](#).

### Co-movements in the highest frequency band (1 week – 3 months)

The highest frequency band is characterized by numerous areas of significant co-movements since the beginning of 2006 until the end of the studied period. This means that the same news impacts both of the markets. It is interesting to note that while the US and the Russian stock market exhibit no co-movements at these frequencies since the beginning of the Ukrainian crisis, there are no such changes in the short-term dependencies between the Russian and the German stock market.

### Co-movements in the low frequency band (above 1 year)

Similarly to Figure 1, one might note that since the begging of 2005 a spot of significant coefficients is observed centered at the 1 year line of frequencies. Therefore, it might be concluded that a process of integration has begun at that time. However, it might be also noted that the most strongly pronounced co-movements correspond to frequencies lower than 2.5 years. Those co-movements are observed since the beginning of the investigated period and might be interpreted as presence of long-term relationship. It is hard to determine if this relationship lasts until the end of the period under study, since the respective

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\(^{15}\) At that time the joint venture TNK-BP was one of the biggest vertically integrated oil and gas companies in Russia.
coefficients are inside the cone of influence. These long-term co-movements most probably reflect existing trade relationships of long-run character, such as natural gas imports. *This means that one might expect high degree of integration. Therefore, a crisis in the Russian stock market is likely to be propagated to the German market through existing trade relationships.* This is not an unexpected finding since Russia is one of the major natural gas suppliers of Germany. However, is the probability of crisis propagation reinforced by herd behavior of economic agents, who are already expecting such negative consequences? The answer might be found through a close inspection of the mid-term frequencies since the beginning of the Ukrainian crisis.

**Co-movements in the medium frequency band (3 months – 1 year)**

Going back to Figure 3 it is easily seen that since the beginning of 2014 a spot of significant coefficients is present at the 3 – 6 months frequency band, which indicates that a process of contagion has already begun.

**IV.3.4. Russian – UK stock market co-movements**

The co-movements between the Russian and the UK stock market are presented at Figure 4.

**Co-movements in the highest frequency band (1 week – 3 months)**

There are significant co-movements since the beginning of 2005 until the end of the period under study, which indicates that both of the markets are influenced by the same news. This finding is not surprising in the light of the fact that the LSE is the listing center for considerable number of Russian stocks IPOs.

**Co-movements in the low frequency band (above 1 year)**

A huge area of statistically significant coefficients is noted spanning from the beginning until the end of the investigated period. Even though, the last coefficients are inside the cone of influence, there are no indications for a break in the pattern. Furthermore, this strongly pronounced interdependence between the two markets has its fundamental grounding, as major British oil companies have considerable investments in Russia. Hence, one might expect that an occurrence of crisis in the Russian stock market will be transferred to the UK market through the existing trade and investment relationships.

**Co-movements in the medium frequency band (3 months – 1 year)**

It is interesting to note that similarly to the German market, a spot of significant wavelet coherency coefficients, corresponding to the 4 – 8 months frequency band, is present since the end of 2013. The increased co-movement between the Russian and the UK stock market since the beginning of the Ukrainian crisis, might be interpreted as a signal of contagion.

**IV.3.5. Russian – French stock market co-movements**

The co-movements between the Russian and the French stock market are presented at Figure 5.
Significant high frequency co-movements are identified since the beginning of 2006, whose interpretation is similar to that of the high frequency co-movements presented at Figure 3.

**Co-movements in the low frequency band (above 1 year)**

An analysis of the low frequency co-movements indicate presence of long-term relationship between the two markets. However, it might be noted that since the end of 2012 there is a break in the area of the significant coefficients, suggesting weakening in the degree of stock market integration. Therefore, crisis propagation through market fundamentals is less likely to occur as compared to the UK and the German stock markets.

**Co-movements in the medium frequency band (3 months – 1 year)**

It is interesting to note that a spot of significant co-movements covering spanning during the Eurozone debt crisis is present, which is indicative of spillover effects during that time. Considering the influence of the recent geopolitical events, an indication of contagion might be concluded, as an area of significant coefficients corresponding to the frequency band of 6 - 9 months is observed since the beginning of 2014.

IV.3.6. Russian – Italian stock market co-movements

The co-movements between the Russian and the Italian stock market are presented at Figure 6.

**Co-movements in the highest frequency band (1 week – 3 months)**

There are some high frequency co-movements since 2006, even though there are less intense as compared to the respective co-movements between the Russian and the UK as well as the Russian and the German stock markets.

**Co-movements in the low frequency band (above 1 year)**

While in the beginning of the investigated period the observed significant co-movements suggest integration of the stock markets of Russia and Italy, a transition to segmentation might be noted since 2012. This finding implies that an occurrence of crisis at the Russian stock market is not likely to be transferred to the Italian market through fundamental relationships.

**Co-movements in the medium frequency band (3 months – 1 year)**

Significant co-movements are present during the Eurozone crisis and in particular, since Sep-2011 with the downgrade of the Italian debt, an area of significant coefficients corresponding to the 3 – 6 months frequency band appears, indicating contagion from the Italian to the Russian market. However, after the end of 2012 no significant co-movements are present, which means that there are no indications of spillover effects of the recent Russian stock market downturn to the Italian stock market.

V. Concluding remarks: Crisis spillover perspectives

The findings of the performed empirical work and analysis might be summarized as follows. First of all, according to the research results, the stock markets of Germany and the
UK are exposed at the highest risk of negative spillover effects in case the Russian equity market crashes. On one hand, the crisis is likely to propagate through the existing markets’ fundamentals. On the other hand, indications of contagious effects associated with the recent downturn of the Russian stock market are identified, which are probably due to behavioral biases of the economic agents. As compared to the German and the UK stock market, the French equity market seems to be exposed at lesser risk, even though some indications of contagion were found. Finally, the US and the Italian stock market are found to be highly segmented from the Russian stock market since 2012 and therefore, a crisis in the Russian stock market is not likely to be propagated through fundamental relationships. In addition, no signs of contagion are observed. However, even though the US and the Italian direct exposure suggests no threats of spillover effects, it should be noted that an occurrence of a crisis in the Russian stock market could indirectly affect both of the markets through their existing relationships with the stock markets of Germany and the UK.

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Appendix A

Table 1. List of investigated stock market indices.

<table>
<thead>
<tr>
<th>Index</th>
<th>Country</th>
<th>Data source</th>
</tr>
</thead>
</table>

Table 2. Descriptive statistics of the investigated log-return series.

<table>
<thead>
<tr>
<th></th>
<th>RTS</th>
<th>S&amp;P 500</th>
<th>DAX</th>
<th>FTSE 100</th>
<th>CAC 40</th>
<th>FTSE MIB</th>
</tr>
</thead>
<tbody>
<tr>
<td>№ of obs.</td>
<td>550</td>
<td>550</td>
<td>550</td>
<td>550</td>
<td>550</td>
<td>550</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0012</td>
<td>0.0010</td>
<td>0.0015</td>
<td>0.0007</td>
<td>0.0003</td>
<td>-0.0005</td>
</tr>
<tr>
<td>STD</td>
<td>0.0506</td>
<td>0.0250</td>
<td>0.0309</td>
<td>0.0253</td>
<td>0.0302</td>
<td>0.0339</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.4444</td>
<td>-0.9794</td>
<td>-1.1173</td>
<td>-1.5336</td>
<td>-1.3518</td>
<td>-1.3162</td>
</tr>
<tr>
<td>ADF test</td>
<td>-21.5901 (\ast)</td>
<td>-24.6788 (\ast)</td>
<td>-25.6767 (\ast)</td>
<td>-26.0943 (\ast)</td>
<td>-26.4049 (\ast)</td>
<td>-24.9753 (\ast)</td>
</tr>
</tbody>
</table>

\(\ast\) The reported Dickey – Fuller test statistic is statistically significant at 1% level of significance.

Figure 7: Weekly closing prices of (a) RTS, (b) S&P 500, (c) DAX, (d) FTSE 100, (e) CAC 40, (f) FTSE MIB.
Appendix B

Table 3. Capitalization and liquidity indicators of the Russian stock market. 13

<table>
<thead>
<tr>
<th>Year</th>
<th>Market cap (in mln USD)</th>
<th>Market cap (% of GDP)</th>
<th>Stock traded (% of GDP)</th>
<th>Turnover ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>267,957</td>
<td>45.3</td>
<td>22.1</td>
<td>52.5</td>
</tr>
<tr>
<td>2005</td>
<td>548,579</td>
<td>71.8</td>
<td>20.9</td>
<td>39.0</td>
</tr>
<tr>
<td>2006</td>
<td>1,057,189</td>
<td>106.8</td>
<td>52.0</td>
<td>64.1</td>
</tr>
<tr>
<td>2007</td>
<td>1,503,011</td>
<td>115.6</td>
<td>58.1</td>
<td>58.9</td>
</tr>
<tr>
<td>2008</td>
<td>397,183</td>
<td>23.9</td>
<td>33.9</td>
<td>59.2</td>
</tr>
<tr>
<td>2009</td>
<td>861,424</td>
<td>70.5</td>
<td>55.8</td>
<td>108.5</td>
</tr>
<tr>
<td>2010</td>
<td>1,004,525</td>
<td>67.5</td>
<td>52.4</td>
<td>85.7</td>
</tr>
<tr>
<td>2011</td>
<td>796,376</td>
<td>42.9</td>
<td>60.2</td>
<td>127.3</td>
</tr>
<tr>
<td>2012</td>
<td>874,659</td>
<td>43.4</td>
<td>36.3</td>
<td>87.6</td>
</tr>
</tbody>
</table>

Note: The presented data is collected from the official site of the World Bank: http://data.worldbank.org/indicator.

Industry Cumulative weight

<table>
<thead>
<tr>
<th>Industry</th>
<th>Cumulative weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil &amp; Gas</td>
<td>49.44%</td>
</tr>
<tr>
<td>Banking</td>
<td>17.75%</td>
</tr>
<tr>
<td>Metals &amp; Mining</td>
<td>10.62%</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>9.30%</td>
</tr>
<tr>
<td>Retail</td>
<td>7.16%</td>
</tr>
<tr>
<td>Other</td>
<td>5.73%</td>
</tr>
<tr>
<td>Utilities</td>
<td>2.42%</td>
</tr>
</tbody>
</table>

Note: Cumulative weights are calculated by the author based on the individual stock weights valid from 17-Jun-2014 to 15-Sep-2014, published by the Moscow Exchange at the following web address: http://moex.com/s777.

Figure 8: Russian stock market benchmark indices’ constituent weights, aggregated by industries 13.