Brunel University London
Department of
Economics and Finance

Economics and Finance Working Paper Series

Working Paper No. 17-16

Guglielmo Maria Caporale and Nurdaulet Abilov

The Spillovers between the Russian and Other Asian and European Stock Markets
A Multivariate GARCH-in-Mean Analysis

July 2017

http://www.brunel.ac.uk/economics

SPILLOVERS BETWEEN THE RUSSIAN AND OTHER ASIAN AND EUROPEAN STOCK MARKETS: A MULTIVARIATE GARCH-IN-MEAN ANALYSIS

Guglielmo Maria Caporale

Brunel University London

Nurdaulet Abilov

Higher School of Economics, Moscow

July 2017

Abstract

This paper uses a VAR-GARCH-in mean framework with a BEKK representation to examine spillovers between the Russian and other Asian and European markets, distinguishing between emerging and developed markets. The aggregate estimates suggest the presence of mean spillovers from Europe towards Russia during the crisis period only, whilst there are volatility spillovers from both Europe and Asia. There are also GARCH-in-mean effects from the developed Asian markets and volatility spillovers from the emerging ones. As for the European markets, there are mean spillovers towards Russia from the developed ones and volatility spillovers from the emerging ones. Concerning spillovers in the opposite direction, i.e. from the Russian market, there is evidence of both mean and volatility spillovers affecting both types of Asian markets (though the emerging ones to a greater extent), but only the emerging ones in the case of Europe.

Keywords: Russian stock market, spillovers, VAR-GARCH-in-mean, BEKK representation

JEL Classification: G15, C32

Corresponding author: Professor Guglielmo Maria Caporale, Department of Economics and Finance, Brunel University, London, UB8 3PH, UK. Tel.: +44 (0)1895 266713. Fax: +44 (0)1895 269770. Email: Guglielmo-Maria.Caporale@brunel.ac.uk

1. Introduction

There is plenty of evidence suggesting that stock market spillovers play an important role in both normal and turmoil periods (see, e.g., Caporale et al., 2005, 2006). This paper focuses on the linkages between the Russian and other Asian and European stock markets, providing new empirical evidence that is of interest to both academics and investors. Consider, for instance, a Russian trader dealing in derivatives, whose price is affected by the volatility of the underlying asset, who should decide whether to adopt a positive or negative vega strategy, which are appropriate for periods of high and low volatility respectively. If there are spillovers from some other highly volatile Asian stock market that the trader is not aware of, he might wrongly bet on low volatility and choose a negative vega strategy, and will then experience huge losses owing to the high volatility of Russian stocks resulting from those spillovers. Alternatively, suppose there are mean spillovers from some European market that is in free fall; this will lead to lower Russian stock prices, and traders will postpone the purchase of Russian stocks to buy them cheap after the stock market falls if they are aware of these linkages.

The present study estimates trivariate VAR-GARCH-in-mean models with a BEKK representation to test for both mean and volatility spillovers between the Russian and other Asian and European stock markets. Two additional models are estimated distinguishing between emerging and developed countries in the case of Asia and Europe respectively; this distinction, as well as the fact that GARCH-in-mean effects are incorporated, sheds new light on the linkages between these markets compared to previous studies on Russia (see, e.g., Saleem, 2008, and Oikonomiku, 2016); moreover, we include in the analysis a much wider set of countries. The layout of the paper is as follows. Section 2 briefly reviews the relevant literature on the Russian stock market. Section 3 outlines the empirical framework and the hypotheses to be tested. Section 4 discusses the data and the empirical findings. Section 5 offers some concluding remarks.

2. Literature Review

Some studies focus on spillovers from global and regional to local emerging markets (e.g., Beirne et al., 2010). Saleem (2008) analyses specifically spillovers from global to the Russian stock market, and also how the Russian debt crisis in 1998 affected the transmission channels. Beirne et al. (2010) find in most cases spillover effects from regional and global stock markets to local emerging ones, but the relative importance of global and regional markets as well as of the different transmission channels differ across regions. In the case of Russia, they conclude that mean spillovers are not present, but they find evidence of own and cross-market GARCH-in-mean as well as variance spillovers. Beirne et al. (2013) study spillovers and contagion for emerging market economies and conclude that volatility spillovers exist for almost all countries, including Russia. Caporale and Spagnolo (2010) investigate the integration of the stock markets of the CEECs, Russia and the UK and find evidence of both mean and volatility spillovers from Russia to the CEECs. Ločmelis and Mititel (2015) study interdependence between the Russian, EU and US stock markets during the 2014-2015 Russian crisis, and find mean spillovers from the EU and US stock markets to the Russian one estimating impulse response functions, and also that volatility spillovers towards the Russian stock market strengthened during the crisis. All these papers use VAR-GARCH-in-mean specifications with the BEKK representation proposed by Engle and Kroner (1995).

A more recent paper by Oikonomiku (2016) employs instead a VAR-EGARCH model to examine mean and volatility linkages between four countries including Russia. He finds that there are bidirectional linkages between mean returns in the Russian stock market and those of the Czech Republic, Poland and Ukraine, and that the volatility of Russian stock prices is highly persistent. However, his EGARCH specification does not allow for GARCH-in-mean effects.

One important issue is the distribution followed by the error term in the mean equation, since non-normality makes the estimates of the standard errors (and therefore statistical inference) invalid. Beirne et al. (2010, 2013) address it by using the quasi-maximum likelihood (QML) estimator of Bollerslev and Wooldridge (1992), which is robust to the distribution of the innovation terms. Alternatively, one can assume a different distribution and use other estimation methods. For example, Harvey and Lange (2015) assumed a t-distribution and a generalized error distribution (GED) when estimating their univariate EGARCH model on the grounds that these are more suitable for the innovations when the tail index parameter goes to infinity; however, the multivariate GED extension is computationally difficult to implement. Heracleous (2003) compared the performance of GARCH models under the normality and t-distribution assumptions for the return series, and concluded that the latter is more suitable. Rossi and Spazzini (2008) also found that a multivariate GARCH-BEKK model with the latter distributional assumption outperforms a specification based on the normality assumption owing to the fat tails of the return distributions.

3. Empirical Framework

3.1 The Model

To test for own and cross-market spillover effects a VAR-GARCH(1,1)-in-mean with a BEKK representation is used. In particular, the following three models are estimated:

i) Model 1 examines spillovers vis-à-vis other Asian and European stock markets. The adopted VAR-GARCH(1,1)-in-mean specification is the following:

$$\boldsymbol{x_t} = \boldsymbol{\alpha} + \boldsymbol{B}'\boldsymbol{x_{t-1}} + \boldsymbol{\Lambda}'\boldsymbol{h_t} + \boldsymbol{\delta f_{t-1}} + \boldsymbol{u_t} \quad (1)$$

$$\boldsymbol{x_t} = \begin{bmatrix} x_{1,t} \\ x_{2,t} \\ x_{3,t} \end{bmatrix} \quad \boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} \quad \boldsymbol{B} = \begin{bmatrix} B_{11} & \beta_{12} & \beta_{13} \\ B_{21} & \beta_{22} & \beta_{23} \\ B_{31} & \beta_{32} & \beta_{33} \end{bmatrix}$$

$$\boldsymbol{\Lambda} = \begin{bmatrix} \lambda_{11} & 0 & 0 \\ \lambda_{21} & 0 & 0 \\ \lambda_{31} & 0 & 0 \end{bmatrix} \quad \boldsymbol{h_t} = \begin{bmatrix} h_{11,t} \\ h_{21,t} \\ h_{31,t} \end{bmatrix} \quad \boldsymbol{u_t} = \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \end{bmatrix}$$

$$\boldsymbol{\delta} = \begin{bmatrix} \delta_{11} & \delta_{12} \\ \delta_{21} & \delta_{22} \\ \delta_{31} & \delta_{32} \end{bmatrix}$$

where $\boldsymbol{x_t}$ is a trivariate vector including stock returns for Russia and other Asian and European markets, $\boldsymbol{\alpha}$ is a vector of constants; $\boldsymbol{h_t}$ is the conditional variance-covariance matrix of stock index returns; $\boldsymbol{\Lambda}$ is a matrix of coefficients representing the GARCH-in-mean effects, and the effects of own-market and cross-market variances on returns in the Russian stock market assuming that their volatility does not affect mean returns in Asia and Europe; $\boldsymbol{f_{t-1}}$ is a vector including US stock returns and the 90-day US Treasury Bill rate as control variables in the mean equation; $\boldsymbol{\delta}$ is a 2x3 matrix whose coefficients measure the effects of changes in the control variables on market returns. The coefficients in the matrix $\boldsymbol{B}$ in upper case letters are defined as follows:

$$B_{11} = \beta_{11} + \beta_{1d} \quad (2)$$

$$B_{21} = \beta_{21} + \beta_{2d} \tag{3}$$

$$B_{31} = \beta_{31} + \beta_{3d} \tag{4}$$

where β_{1d} , β_{2d} and β_{3d} are the coefficients of a dummy variable with a switch on 15 September 2008, the day when Lehman Brothers collapsed; this allows for a possible structural break at the onset of the global financial crisis.

For the conditional variance-covariance matrix a BEKK representation is adopted as follows:

$$\boldsymbol{u_t} | I_{t-1} \sim t_\nu(\boldsymbol{0}, \boldsymbol{H_t})$$

$$\boldsymbol{H_t} = \boldsymbol{C_0 C_0'} + \boldsymbol{A' \varepsilon_{t-1} \varepsilon_{t-1}' A} + \boldsymbol{G' H_{t-1} G} \tag{5}$$

$$\boldsymbol{\varepsilon_{t-1}} = \begin{bmatrix} e_{1,t-1}^2 & e_{1,t-1}e_{2.t-1} & e_{1,t-1}e_{3.t-1} \\ e_{2,t-1}e_{1.t-1} & e_{2,t-1}^2 & e_{2,t-1}e_{3.t-1} \\ e_{3,t-1}e_{1.t-1} & e_{3,t-1}e_{2.t-1} & e_{3,t-1}^2 \end{bmatrix}$$

$$\boldsymbol{H_t} = \begin{bmatrix} h_{11,t} & h_{12,t} & h_{13,t} \\ h_{21,t} & h_{22,t} & h_{23,t} \\ h_{31,t} & h_{32,t} & h_{33,t} \end{bmatrix} \boldsymbol{C_0} = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix}$$

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad \boldsymbol{G} = \begin{bmatrix} g_{11} & g_{21} & g_{31} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix}$$

The return series are assumed to follow Student's t-distribution, where $t_\nu(\boldsymbol{0}, \boldsymbol{H_t})$ stands for a t-distribution with a zero mean, a conditional variance-covariance matrix given by $\boldsymbol{H_t}$ and ν degrees of freedom; $\boldsymbol{\varepsilon}$ (the sample counterpart to $\boldsymbol{u}$) is a vector of residuals from the conditional mean equation***;*** ***A*** and ***G*** are matrices of coefficients representing ARCH and GARCH effects respectively in the conditional variance equation - these measure the impact of own-market and cross-market volatilities.

The probability density function is that corresponding to the t-distribution for the innovation terms, and the maximum likelihood estimation is carried out using a numeric search algorithm:

$$f(\boldsymbol{x_t} | I_{t-1}; \boldsymbol{\theta}) = \frac{\Gamma\left(\frac{\nu+n}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)[\pi(\nu-2)]^{n/2}} \; |\boldsymbol{H_t}|^{-\frac{1}{2}} \left(1 + \frac{\boldsymbol{u_t'} \, |\boldsymbol{H_t}|^{-1} \boldsymbol{u_t}}{\nu-2}\right)^{-\frac{n+\nu}{2}} \tag{6}$$

where ν is the number of degrees of freedom of the multivariate t-distribution, n is the number of equations in the VAR system or the number of rows of the vector $\boldsymbol{x_t}$, and $\Gamma(.)$ is the usual gamma function. The model is estimated by maximising the log-likelihood function with respect to the vector of parameters $\boldsymbol{\theta}$. This function is shown below (see Rossi and Spazzini, 2008 for more details on this estimation method):

$$\mathcal{L}(\boldsymbol{\theta}) = \sum_{t=2}^{T} logL(\boldsymbol{\theta}|\boldsymbol{x_t}) = (T-1)log\Gamma\left(\frac{\nu+n}{2}\right) - (T-1)log\Gamma\left(\frac{\nu}{2}\right) -$$

$$-\frac{n(T-1)}{2}log\pi - \frac{n(T-1)}{2}log(\nu-2) - \frac{1}{2}\sum_{t=2}^{T}\log|\boldsymbol{H_t}| - \frac{\nu+n}{2}\sum_{t=2}^{T}log\left(1+\frac{\boldsymbol{u}_t'\,|\boldsymbol{H_t}|^{-1}\boldsymbol{u_t}}{\nu-2}\right) \quad (7)$$

ii) Model 2 examines spillovers vis-à-vis a number of Asian stock markets dividing them into two subsets, namely emerging and developed ones. The VAR-GARCH-in-mean specification with a BEKK representation is the same as before:

$$\boldsymbol{x_t} = \boldsymbol{\alpha} + \boldsymbol{B}'\boldsymbol{x_{t-1}} + \boldsymbol{\Lambda}'\boldsymbol{h_t} + \boldsymbol{\delta f_{t-1}} + \boldsymbol{u_t} \quad (8)$$

$$\boldsymbol{u_t}|\, I_{t-1} \sim t_\nu(\boldsymbol{0},\boldsymbol{H_t})$$

$$\boldsymbol{H_t} = \boldsymbol{C_0C_0'} + \boldsymbol{A}'\boldsymbol{\varepsilon_{t-1}\varepsilon_{t-1}'A} + \boldsymbol{G}'\boldsymbol{H_{t-1}G} \quad (9)$$

However, in this case $\boldsymbol{x_t}$ is a 3x1 vector including returns for the Russian stock market, emerging Asian markets and developed Asian markets; also, $\boldsymbol{f_{t-1}}$is now a vector including an additional control variable, i.e. European stock returns.

iii) Model 3. In this case, the Russian, developed and emerging European markets are included in the trivariate model, and the third control variable is Asian stock returns.

3.2 Hypothesis Testing

The hypotheses of interest are tested carrying out Wald tests:

$$W = [\boldsymbol{R\hat{\theta}}]'\left[\boldsymbol{RVar}(\boldsymbol{\hat{\theta}})\boldsymbol{R}'\right]^{-1}[\boldsymbol{R\hat{\theta}}] \quad (10)$$

where R is a qxk matrix, q is the number of restrictions and k is the number of explanatory variables; $\hat{\theta}$ is the kx1 vector of the estimated coefficients, and $Var(\hat{\theta})$ their variance-covariance matrix. The test statistic has a chi-square distribution under the null hypothesis with the number of degrees of freedom equal to the number of restrictions.

The relevant hypotheses are the following in the case of *Model 1*:

Mean spillovers

H01: No spillovers in mean from Asia to Russia: $\beta_{21} = \beta_{2d} = 0$.

H02: No spillovers in mean from Europe to Russia: $\beta_{31} = \beta_{3d} = 0$.

H03: No spillovers in mean from Asia and Europe to Russia: $\beta_{21} = \beta_{31} = \beta_{2d} = \beta_{3d} = 0$

H04: No spillovers in mean from Russia to Asia: $\beta_{12} = 0$

H05: No spillovers in mean from Russia to Europe: $\beta_{13} = 0$

Volatility spillovers

H06: No volatility spillovers from Asia: $a_{21} = g_{21} = 0$.

H07: No volatility spillovers from Europe: $a_{31} = g_{31} = 0$.

H08: No volatility spillovers from Asia and Europe: $a_{21} = g_{21} = a_{31} = g_{31} = 0$.

H09: No volatility spillovers from Russia towards Asia: $a_{12} = g_{12} = 0$

H10: No volatility spillovers from Russia towards Europe: $a_{13} = g_{13} = 0$

GARCH-in-mean effects

H11: No GARCH-in-mean effects from volatility to mean returns: $\lambda_{11} = 0$.

H12: No GARCH-in-mean effects from volatility in Asian stock markets to mean returns in the stock market Russia: $\lambda_{21} = 0$

H13: No GARCH-in-mean effects from volatility in European stock markets to mean returns in the stock market of Russia: $\lambda_{31} = 0$

H14: No GARCH-in-mean effects whatsoever: $\lambda_{11} = \lambda_{21} = \lambda_{31} = 0$

The corresponding hypotheses are also tested for *Model 2* (spillovers between Russia, emerging and developed Asian markets - H15 to H28) and *Model 3* (spillovers between Russia, emerging and developed European markets - H29 to H42).

4. Data and Empirical Results

4.1 Data Description

The dataset consists of weekly closing index points for Friday from 7 January 2000 to 31 December 2015 for the following countries:[1]

Asia: China, Hong Kong, India, Indonesia, Israel, Japan, Malaysia, Pakistan, Philippines, Singapore, South Korea, Thailand;

Europe: Belgium, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Romania, Russia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom.

The data source is Thompson Reuters Datastream. Weekly returns are calculated in domestic currency as:

$$x_t^i = log\, P_t^i - \; log\, P_{t-1}^i \qquad (11)$$

where x_t^i stands for returns in country i in week t, P_t^i being the corresponding stock market index. Weekly data have been chosen instead of daily ones to avoid the problem of asynchronous trading that could bias the results: stock exchanges in different parts of the world close at different times on a given day, which results in a significant mismatch between the times when daily returns are measured in different regions; since we aim to analyse spillovers between stock markets in several regions, spillovers would either be missed or recorded at an incorrect time if daily data were used.

---

[1] The following is the list of countries in the sample with the corresponding stock indexes shown in parentheses: Belgium (BEL20), Croatia) CROBEX, Czech Republic PX Index), Denmark (OMX Copenhagen 20), Estonia (OMX Tallinn), Finland (OMX Helsinki 25), France (CAC 40), Germany (DAX), Greece (Athex General Share Price Index), Hong Kong (Hang Seng), Hungary (Budapest SE) , India (BSE Sensex Index), Italy (FTSE MIB), Japan (Topix), Latvia (OMX Riga), Lithuania (OMX Vilnius), Malaysia (Thompson Reuters Malaysia Index), Netherlands (AEX), Norway (Oslo Stock Exchange Equity Index), Israel (Thompson Reuters Israel Index), Indonesia (Jakarta SE Composite Index), Pakistan (Thompson Reuters Pakistan Index), Philippines (Philippine Stock Exchange PSEi Index), Poland (Warsaw SE WIG Poland Index), Portugal (Euronext Lisbon PSI 20 Index), Romania (Bucharest SE BET Index), Russia (MICEX), Singapore (FTSE Straits Times Index), South Korea (Korea SE Kospi Index), Spain (IBEX 35 Index), Sweden (OMX Stockholm 30 Index), Switzerland (Swiss Market Index), Thailand (SET Index), Turkey (BIST 100 Index), Ukraine (PFTS Index), United Kingdom (FTSE 100) and USA (S&P 500).

In *Model 1*, the return series for the Asian (European) stock market is the GDP-weighted average of stock returns in the individual countries in the region. Annual GDP in 2010 constant dollars was obtained for each Asian and European country in the sample (also from Thompson Reuters Datastream). Then we converted annual GDP into weekly series and the GDP-weight for a particular country is calculated as the 104-week moving average. Ideally one would have used instead stock market capitalisation to determine the weights, but this was not available for most countries.

In Model 2 the Asian countries in the sample are divided into two groups:

1) Emerging markets: China, India, Indonesia, Pakistan, Philippines, Thailand;
2) Developed markets: Hong Kong, Israel, Japan, Malaysia, Singapore, South Korea.

and aggregate returns for each subset are calculated as before.

Similarly, in Model 3 the European countries are divided into the two following groups:

1) Emerging markets: Croatia, Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Poland, Romania, Turkey, Ukraine;
2) Developed markets: Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom.

and again aggregate returns are constructed as before.

The return series are plotted in Figures 1, 2, and 3 in the Appendix. The impact of the global financial crisis in September/October 2008 is clearly visible and motivates the inclusion of a switch dummy to model this structural break. Descriptive statistics are reported in Table 1. In all cases mean returns are close to zero and exhibit large kurtosis with negative skewness; the Jarque-Bera test statistics imply rejection of the null of normality in all cases. Therefore, as already mentioned, we use a Student's t-distribution instead.

4.2 Empirical Results

The estimation results for *Model 1* are reported in Table 2 and 3. Most coefficients in the mean equation are not significant; however, there is evidence of European returns affecting the Russian ones during the crisis period only, and of both Russian and US returns affecting the Asian ones. The US T-bill rate is also insignificant. As for the conditional variance equation, volatility appears to be highly persistent in all three markets, and most coefficients are significant, but there is no evidence of volatility spillovers from the Russian to the other stock markets.

The Wald test statistics are reported in Table 8 and 9. We find some evidence of spillovers from European mean returns to the Russian ones (H02), but only in the crisis period, and of spillovers from Asia as well (H01), whilst the joint null of mean spillovers from Asia and Europe is rejected (H03). By contrast, the joint null of volatility spillovers from Asia and Europe towards Russia (H08) cannot be rejected; the null of no spillovers from Asia (H06) and Europe (H07) can be rejected at the 5% and 10% level respectively.

We also find evidence of mean spillovers from Russia towards the Asian stock markets (H04). Finally, no GARCH-in-mean effects are found.

The results for *Model 2* are shown in Table 4 and 5. Again most coefficients are not significant in the mean equation, but GARCH-in-mean effects are found in this case. The Wald test statistics (see Table 8) suggest spillovers from the Asian markets; however, mean spillovers do not appear to be present (H15, H16), consistently with the results from *Model 1*. By contrast, there is evidence of GARCH-in-mean effects from the developed Asian markets (H27), but not from the emerging ones (H26). There is also evidence of mean spillovers from the Russian stock market towards the developed Asian markets (H19) and volatility spillovers towards both the emerging and developed Asian markets (H23, H24).

Volatility again is found to be highly persistent (see Table 5). The joint null of no volatility spillovers from emerging and developed Asian markets (H22) is strongly rejected, once more consistently with the results from *Model 1*. The statistical tests suggest that the significant volatility spillovers are more specifically those from emerging Asia (H20). On the whole, we find both mean and volatility spillovers from Asia towards Russia. There is also evidence of mean spillovers from the Russian stock market towards the developed Asian markets (H19) and volatility spillovers towards both the emerging and developed Asian markets (H23, H24).

The estimated coefficients for *Model 3* are shown in Table 6 and 7. They suggest significant mean spillovers from Europe, as also confirmed by the Wald test for emerging and developed European markets jointly (H31 – see Table 8). More specifically, there is no evidence of mean spillovers from the emerging European markets (H29), but spillovers from the developed ones (H30) are found. There is also evidence of significant volatility spillovers from Europe, which is confirmed by the Wald test for emerging and developed European markets jointly (H36) (see Table 14). Further testing shows that these spillovers are from the emerging (H34) rather than developed (H35) European markets (see Table 8). Table 8 also shows that there are mean spillovers from the Russian stock market towards the European emerging markets (H32), but not the developed ones (H33). Finally, no GARCH-in-mean effects are found (see Table 9).

5. Conclusions

This paper uses a VAR-GARCH-in mean framework with a BEKK representation to examine spillovers between the Russian and other Asian and European markets. Additional estimates are obtained after dividing each of these two regions into two sets of countries (emerging and developed) in order to shed further light on the linkages between these markets; further, possible GARCH-in-mean effects are taken into account, and a wide set of countries is considered. These features of the analysis improve upon earlier studies on Russia (e.g., Saleem, 2008, and Oikonomiku, 2016) by producing more informative results.

The aggregate estimates suggest the presence of mean spillovers from Europe towards Russia during the crisis period only, whilst there are volatility spillovers from both Europe and Asia. The results based on distinguishing between emerging and developed markets in Asia and Europe respectively reveal GARCH-in-mean effects from the developed Asian markets and volatility spillovers from the emerging ones. As for the European markets, there are mean spillovers towards Russia from the developed ones and volatility spillovers from the emerging ones.

Overall, it appears that Russian mean returns are affected by those of (Asian and European) developed markets, whilst both returns themselves and their volatility respond to volatility changes in emerging markets (again Asian and European). Essentially, there are three possible types of linkages: 1) from external mean returns to Russian mean returns; 2) from external return volatility to Russian mean returns; 3) from external to Russian return volatility. Our results suggest that the first are found with the developed European markets, the second with the developed Asian markets, and the third, the strongest ones, predominantly with both Asian and European emerging markets (to a lesser extent with developed markets). Concerning spillovers in the opposite direction, i.e. from the Russian market, there is evidence of both mean and volatility spillovers affecting both types of Asian markets (though the emerging ones to a greater extent), but only the emerging ones in the case of Europe. This represents new evidence that is relevant not only to academics but also to investors having to choose portfolio management strategies.

References

Bae, K.-H., Karolyi, G.A.,1994. "Good news, bad news and international spillovers of stock returns between Japan and the US", *Pacific-Basin Finance Journal* 2, 405-438.

Beirne, J., Caporale, G.M., Schulze-Ghattas, M. and N. Spagnolo (2010), "Global and regional spillovers in emerging stock markets: a multivariate GARCH-in-mean analysis", *Emerging Markets Review*, 11, 250-260.

Beirne, J., Caporale, G.M., Schulze-Ghattas, M. and N. Spagnolo (2013), "Volatility spillovers and contagion from mature to emerging stock markets", *Review of International Economics*, 21, 5, 1060-1075.

Berndt, E., B. Hall, R. Hall and J. Hausman, 1974, "Estimation and inference in nonlinear structural models", *Annals of Economics and Social Measurement*, 4, 653-665.

Bollerslev, T.P., 1986, "General Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, 31, 309-328.

Bollerslev, T., Wooldridge, J.M., 1992. "Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances", *Econometric Reviews* 11 (2), 143-172.

Caporale, G.M. and N. Spagnolo, 2010, "Stock market integration between three CEECs, Russia and the UK", CESifo working paper Monetary Policy and International Finance, No. 2978

Caporale, G.M., Cipollini, A. and N. Spagnolo (2005), "Testing for contagion: a conditional correlation analysis", Journal of Empirical Finance, 12, 3, 476-489.

Caporale, G.M., Pittis, N. and N. Spagnolo (2006), "Volatility transmission and financial crises", Journal of Economics and Finance, Fall issue, 30, 3, 376-390.

Dayioğlu,T., 2012, "Forecasting Overnight Interest Rates Volatility with Asymmetric GARCH Models", *Journal of Applied Finance & Banking*, vol. 2, no. 6, 2012, 151-162.

Engle, R.F., Gallo, G., Velucchi, M., 2008. "A MEM-based analysis of volatility spillovers in East Asian financial markets", *Econometrics Working Papers Archive*, WP 2008_09, Universita' degli Studi di Firenze, Dipartimento di Statistica "G. Parenti".

Engle, R.F. and K.F. Kroner, 1995, "Multivariate Simultaneous Generalized ARCH", *Econometric Theory*, 11: 122-150.

Giller, G., 2005, "A generalized error distribution", *SSRN Electronic Journal*

King, M., Wadhwani, S., 1990. "Transmission of volatility between stock markets", *Review of Financial Studies* 3 (1), 5-33.

Liu, Y.A. and M.S. Pan, 1997, "Mean and Volatility Spillover Effects in the U.S. and Pacific- Asian Stock Markets," *Multinational Finance Journal*, 1, 47-62.

Ljung, G.M., Box, G. E. P., 1978. "On a measure of lack of fit in time series models", *Biometrika* 65, 297-303.

Ločmelis, K. and D. Mititel, 2015, " Impact of Russia's 2014–2015 Crisis on the Dynamic Linkages between the Stock Markets of Russia, the EU and U.S." , Bachelor Thesis, SSE Riga.

Oikonomikou, L. E.,2016, "Modeling financial market volatility in transition markets: A multivariate case, Courant Research Centre: Poverty, Equity and Growth", Discussion Papers, No. 204

Rossi, E. and F. Spazzini, 2008, "Model and distribution uncertainty in Multivariate GARCH estimation: a Monte Carlo analysis", Quaderni di Dipartimento, EPMQ, Università degli Studi di Pavia, No. 208

Saleem, K. (2008), "International linkage of the Russian market and the Russian financial crisis: A multivariate GARCH analysis", *BoFit Discussion Papers*.

Theodossiou, P. and U. Lee, 1993, "Mean and Volatility Spillovers across Major National Stock Markets: Further Empirical Evidence", *Journal of Financial Research*, 16, 337-350.

Walti, S., 2003, "Testing for Contagion in International Financial Markets: Which Way to Go?", *FAME Working Paper* No. 92.

Worthington, A., Higgs, H., 2004. "Transmission of equity returns and volatility in Asian developed and emerging markets: a multivariate GARCH analysis", *International Journal of Finance & Economics* 9, 71-80.

Appendix

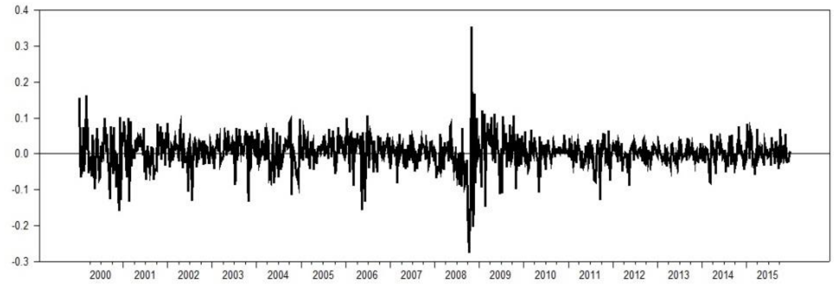

Figure 1: Returns of the stock market of Russia (MICEX)

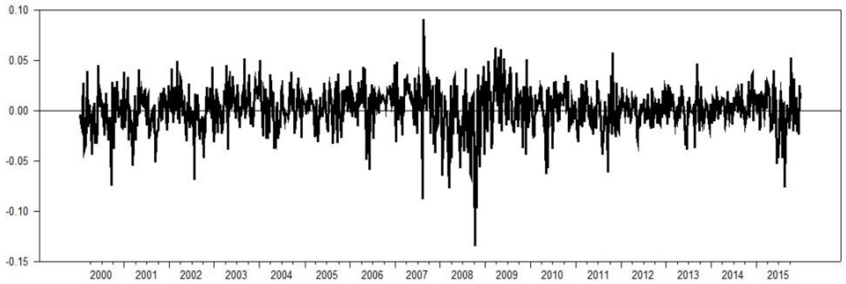

Figure 2: Returns of the Asian stock markets

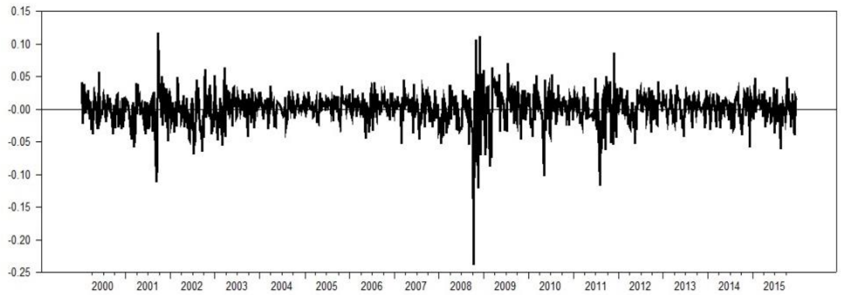

Figure 3**:** Return of the European stock markets

Table 1: Descriptive statistics for returns

	Mean	SD	Skewness	Kurtosis	Jarque-Bera
Russia	0.0026837	0.04646	-0.200775	9.76352	1593.33
Asia	0.0015437	0.02251	-0.727867	5.79388	344.478
Europe	0.0001119	0.02732	-1.14657	11.83472	2891.58

Table 2: Parameter estimates for the mean equation of *Model 1*

	β_{11}	β_{21}	β_{31}	β_{1d}	β_{2d}	β_{3d}	γ_{11}	γ_{21}	γ_{31}	δ_{11}	δ_{12}
Russia	0.015	0.022	-0.055	0.225	-0.830	0.768**	1.887	0.311	-2.311	0.083	0.068
	β_{12}	β_{22}	β_{32}	δ_{21}	δ_{22}						
Asia	0.030*	0.011	-0.0467	0.177***	0.034						
	β_{13}	β_{23}	β_{33}	δ_{31}	δ_{32}						
Europe	0.015	-0.012	-0.098*	0.088	-0.017						

Table 3: Parameter estimates for the variance equation of *Model 1*

	α_{11}	α_{21}	α_{31}	g_{11}	g_{21}	g_{31}
Russia	0.307***	-0.082	0.024	0.945***	0.053***	-0.039
	α_{12}	α_{22}	α_{32}	g_{12}	g_{22}	g_{32}
Asia	0.007	0.141***	0.056*	-0.004	0.990***	-0.021**
	α_{13}	α_{23}	α_{33}	g_{13}	g_{23}	g_{33}
Europe	0.011	-0.015	0.303***	-0.001	0.013***	0.930***

Note: ***, **, and * denote significance at the 1%, 5% and 10% levels respectively.

Table 4: Parameter estimates for the mean equation of *Model 2*

	β_{11}	β_{21}	β_{31}	β_{1d}	β_{2d}	β_{3d}	γ_{11}	γ_{21}	γ_{31}	δ_{11}	δ_{12}	δ_{13}
Russia	0.038	0.001	-0.036	0.240	0.206	0.269	3.842*	5.986	-13.469**	0.049	0.017	-0.030
	β_{12}	β_{22}	β_{32}	δ_{21}	δ_{22}	δ_{23}						
Emerging Asia	0.019	0.029	0.040	0.200***	0.066**	-0.082						
	β_{13}	β_{23}	β_{33}	δ_{31}	δ_{32}	δ_{33}						
Developed Asia	0.038***	0.015	-0.156***	0.100***	0.013	0.083*						

Table 5: Parameter estimates for the variance equation of *Model 2*

	α_{11}	α_{21}	α_{31}	g_{11}	g_{21}	g_{31}
Russia	0.261***	0.052	-0.069	0.974***	-0.122***	0.022
	α_{12}	α_{22}	α_{32}	g_{12}	g_{22}	g_{32}
Emerging Asia	-0.010	0.290***	-0.065	0.014	0.866***	0.053
	α_{13}	α_{23}	α_{33}	g_{13}	g_{23}	g_{33}
Developed Asia	0.040**	-0.018	0.185***	-0.001	-0.053***	0.988***

Note: ***, **, and * denote significance at the 1%, 5% and 10% levels respectively.

Table 6: Parameter estimates for the mean equation of *Model 3*

	β_{11}	β_{21}	β_{31}	β_{1d}	β_{2d}	β_{3d}	γ_{11}	γ_{21}	γ_{31}	δ_{11}	δ_{12}	δ_{13}
Russia	0.026	0.014**	-0.150**	-0.356	-0.108	0.601	1.545	-0.313	-2.130	0.100	0.074	-0.021
	β_{12}	β_{22}	β_{32}	δ_{21}	δ_{22}	δ_{23}						
Emerging Asia	0.019	0.022	-0.010	0.097*	0.042	0.005						
	β_{13}	β_{23}	β_{33}	δ_{31}	δ_{32}	δ_{33}						
Developed Asia	0.011	0.062*	-0.152***	0.094	-0.007	-0.033**						

Table 7: Parameter estimates for the variance equation of *Model 3*

	α_{11}	α_{21}	α_{31}	g_{11}	g_{21}	g_{31}
Russia	0.285***	0.078	-0.054	0.960***	-0.048***	0.006
	α_{12}	α_{22}	α_{32}	g_{12}	g_{22}	g_{32}
Emerging Asia	0.048***	0.159***	0.0515	-0.004	0.976***	-0.029*
	α_{13}	α_{23}	α_{33}	g_{13}	g_{23}	g_{33}
Developed Asia	0.014	-0.017	0.312***	0.001	0.005	0.925***

Note: ***, **, and * denote significance at the 1%, 5% and 10% levels respectively.

Table 8: Wald Test statistics for hypotheses of mean and volatility spillovers

	No spillovers in mean			No spillovers in volatility		
	$\beta_{21} = \beta_{2d} = 0$	$\beta_{31} = \beta_{3d} = 0$	$\beta_{21} = \beta_{2d} = \beta_{31} = \beta_{3d} = 0$	$\alpha_{21} = \alpha_{31} = g_{21} = g_{31} = 0$	$\alpha_{21} = g_{21} = 0$	$\alpha_{31} = g_{31} = 0$
Russia (Model 1)	0.870	5.125*	5.333	13.374***	8.865**	5.240*
Russia (Model 2)	1.224	0.621	3.355	72.155***	32.659***	0.814
Russia (Model 3)	3.892	6.322**	10.650**	17.708***	12.697***	1.321
	$\beta_{12} = \beta_{13} = 0$			$\alpha_{12} = g_{12} = \alpha_{13} = g_{13} = 0$		
Asia and Europe	3.617			1.713		
	$\beta_{12} = 0$	$\beta_{32} = 0$	$\beta_{12} = \beta_{32} = 0$	$\alpha_{12} = \alpha_{32} = g_{12} = g_{32} = 0$	$\alpha_{12} = g_{12} = 0$	$\alpha_{32} = g_{32} = 0$
Asia	3.613*	1.053	1.055	20.993***	0.457	4.562
Emerging Asia	1.362	0.621	3.355	8.899*	3.714	3.986
Emerging Europe	0.870	0.037	0.884	13.623***	9.211***	3.734
	$\beta_{13} = 0$	$\beta_{23} = 0$	$\beta_{13} = \beta_{23} = 0$	$\alpha_{13} = \alpha_{23} = g_{13} = g_{23} = 0$	$\alpha_{13} = g_{13} = 0$	$\alpha_{23} = g_{23} = 0$
Europe	0.737	0.863	2.604	18.179***	0.481	17.322***
Developed Asia	6.900***	0.259	7.378***	78.499***	10.348***	63.835***
Developed Europe	0.340	2.855*	4.051	1.392	1.038	0.180

Note: ***, **, and * denote significance at the 1%, 5% and 10% levels respectively.

Table 9: Wald Test statistics for GARCH-in-mean effects

	No GARCH-in-mean effects			
	$\gamma_{11} = \gamma_{21} = \gamma_{31} = 0$	$\gamma_{11} = 0$	$\gamma_{21} = 0$	$\gamma_{31} = 0$
Model 1	2.878	1.747	0.001	0.149
Model 2	5.459	3.743*	0.861	4.454**
Model 3	1.398	0.719	0.002	0.112

Note: ***, **, and * denote significance at the 1%, 5% and 10% levels respectively.