Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2021.vol8.no8.0297

Regime Dependent Volatility Spillover Effects in Stock Markets Between Kazakhstan and Russia*

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Received: April 20, 2021 Revised: July 04, 2021 Accepted: July 15, 2021

Abstract

In this study, to capture the skewness and kurtosis detected in both conditional and unconditional return distributions of the stock markets of Kazakhstan and Russia, two versions of normal mixture GARCH models are employed. The data set consists of daily observations of the Kazakhstan and Russia stock prices, and world crude oil price, covering the period from 1 June 2006 through 1 March 2021. From the empirical results, incorporating the long memory effect on the returns not only provides better descriptions of dynamic behaviors of the stock market prices but also plays a significant role in improving a better understanding of the return dynamics. In addition, normal mixture models for time-varying volatility provide a better fit to the conditional densities than the usual GARCH specifications and has an important advantage that the conditional higher moments are time-varying. This implies that the volatility skews implied by normal mixture models are more likely to exhibit the features of risk and the direction of the information flow is regime-dependent. The findings of this study contain useful information for diverse purposes of cross-border stock market players such as asset allocation, portfolio management, risk management, and market regulations.

Keywords: Stock Markets, Long Memory Process, Asymmetries, Regime Dependent Spillovers, Bivariate Normal Mixture GARCH Models

JEL Classification Code: C32, C51, G15, G32

1. Introduction

It is not surprising that there are many empirical studies on cross-border links in stock market returns. Empirical modeling of such links is relevant for trading and hedging strategies and provides insights into the transmission of shocks across markets. Previous research has focused on interdependencies in terms of both first and second moments of return distributions, informed by standard asset pricing models and supported by advances in the econometric modeling of volatility.

Russia and Kazakhstan are two large emerging financial markets among the transition economies in the post-Soviet Union. Since having emerged as an important international energy supplier, the petroleum industry has been the primary driving force for the growth of the former Soviet Union region. Fluctuations in oil prices are expected to affect the key macroeconomic variables of these two countries, including their financial markets. Increasing integration of the stock markets leads to complex interdependencies in the returns and volatilities of related markets. Spillover effects between stock markets may arise when information transmission between these markets is neither instantaneous nor complete. The spillover effect is the event in one market due to an event in another market. In other words, spillover effects are events that happen in one context but affect events in another context. The existence of the spillover effect means that the two markets are interconnected and therefore are not isolated. Thus, whatever happens in one market will have an effect on the other market. Hence, understanding the nature of these kinds of spillovers is important for diverse purposes

*Acknowledgements:
The authors would thank Ainur Sundetova for helpful comments on an earlier paper, on which this paper builds. This work was supported by the 2019 Inje University research grant.
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such as asset allocation, portfolio management, and risk management.

There is limited literature focusing on correlation in the returns and volatilities of the cross-border stock markets, especially Kazakhstan and Russia, using different advanced econometric approaches. Huseynov (2010) examined the market structure of the major stock exchanges in eight post-Soviet countries of Armenia, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Uzbekistan, and Ukraine, and observed the similarities and differences among these markets that may be improved through structural changes. There are other studies on the cross-market spillover effects among developed markets or developing markets (Bekaert et al., 2005; Chiang et al., 2007; Cho & Parhizgari, 2008; Celik, 2012; Khan et al., 2020; Alshammari et al., 2020; Le & Tran, 2021). However, most of the research in this area has centered on how changes in crude oil prices affect the stock market. Early influential studies, Jones and Kaul (1996), Sadorsky (1999), have identified a negative relationship between oil prices and stock market returns. Contrarily, Bashar (2006), Mohanty et al. (2011), and Wang et al. (2013) argued that the responses of stock markets to oil shocks depend on the net position of the country in the global oil market and the driving forces of the oil price shocks, suggesting that positive linkages between oil and stock market returns pertain to oil-exporting countries, while negatives ones are registered for oil-importing countries. Recently, in order to examine that the correlations have important implications for asset allocation and portfolio optimization, a strand of studies has focused on the dynamic correlation between oil and stock returns; Miller and Ronald (2009), Reboredo (2010), Filis et al. (2011), Daskalaki and Skiadopoulos (2011), Chang and Yu (2013), Boldanov et al. (2016), Zhu et al. (2017), and Aydogan et al. (2017). Overall, despite the increased interest in the relationship between oil prices and stock market returns, the role of oil prices in deriving linkages between stock markets is not clear.

In this study, to capture the skewness and kurtosis detected in both conditional and unconditional return distributions, two versions of normal mixture GARCH models with the fractionally integrated error correction term in the mean are developed. One is a bivariate normal mixture time-varying GARCH model, which is a generalization of the dynamic conditional correlation (DCC) GARCH proposed by Engle (2002). Another version of the bivariate normal mixture constant correlation GARCH model is an extension of the constant conditional correlation GARCH proposed by Bollerslev (1990). Using recently developed normal mixture GARCH models, this study analyzes how the spillover mechanisms of the Kazakhstan and Russian stock markets work, the degree of substitutability between the two markets, and the dynamics in terms of returns and volatilities, which may be used by the market players.

Compared to previous studies, this study is different in at least four aspects. First, the fractionally integrated error correction term developed by Granger (1986) is considered in the conditional mean. Fractionally integrated series can exhibit long memory, meaning that the correlation between a variable and its own lags decays extremely slowly relative to a VAR. One attraction of long memory processes is that they avoid knife-edge choices between unit-root $I(1)$ processes, which generate complete persistence, and the alternative of stationary and invertible ARMA $I(0)$ processes, which imply relatively rapid exponential decay in their impulse-response weights. Second, in the conditional mean equation, we examine how changes in crude oil prices affect the stock market and how the stock market affects each other in terms of the signs and sizes of the estimated coefficients. Third, as often observed in financial markets, the usual GARCH models with only one possible state for volatility cannot capture enough information of skewness and excess kurtosis in data. In addition, they are not well suited for analyzing time-variation in the conditional higher moments unless it is added exogenously as, for example, in Hansen (1994) and Harvey and Siddique (1999). To overcome these difficulties, multivariate normal mixture GARCH models are used, suggested by Haas et al. (2009) and Chung (2009). Fourth, to consider possible sources of skewness in the returns, the normal mixture GARCH models are extended to include a leverage effect in each variance component, which allows us to draw some new insights about the time-series behavior of the stock market returns.

The remainder of the paper is structured as follows. The next section provides the model specifications, and section III briefly discusses the data and the results of preliminary statistic tests. Section VI analyzes the empirical results concerning the lead and lag effects in the conditional mean, and symmetric and asymmetric time-varying spillover effects in the conditional variances, respectively. The final section contains our concluding remarks.

2. The Model

Let $R_{K,t} = K_t - K_{t-1}$ and $R_{M,t} = M_t - M_{t-1}$ denote Kazakhstan KASE and Russia MOSE stock returns in logarithms at time t, respectively. We assume that they follow fractionally integrated processes, which exhibit long memory and generate very slow decay in the impulse-response weights. Let $y_t = [R_{Kt}, R_{Mt}]'$, the bivariate error correction model in the mean takes the form of;

$$y_t = \Phi_0 + \sum_{a=1}^{q} \Phi_a y_{t-a} + \sum_{b=1}^{n} \Theta_b w_{t-b} + \sum_{c=1}^{n} \Gamma_c x_{t-c} + \varepsilon_t \quad (1)$$

where $\Phi_0 = [\varphi_i]_{i=K,M}$, $\Phi_a = [\phi_{il}^{a}]_{i,l=K,M}$, $\Theta_b = [\theta_i]_{i=K,M}$, $\Gamma_c = [\gamma_i]_{i=K,M}$, w_t denotes WTI oil prices, $x_t = [1-(1-L)^{1-d}](1-L)^d$

Z_t with $d = [d_i]_{i=K,M}$ and $Z_t = K_t - a_0 - a_1M_t$, which is the residuals from the regression of the KASE stock price on the MOEX stock price, and are random residual terms. If the two lag polynomials have roots outside the unit circle, the process is stationary and invertible for $-0.5 < d < 0.5$. The process is said to display long memory when $0 < d < 0.5$. Note that $(1-L)^d = \sum_{k=0}^{\infty} \Gamma(k-d)L^k / [\Gamma(-d)\Gamma(k+1)]$, where $\Gamma(.)$ is the gamma function. The basic properties of fractionally differenced series are discussed in, for example, Granger and Joyeux (1980), and Hosking (1981). If , the KASE stock price tends to be decreasing whereas the MOEX stock price tends to be increasing at time t to maintain the long-term relationship ($Z_t = 0$) between KASE and MOEX stock price. Similarly, when $Z_{t-1} < 0$, the KASE stock price tends to be increasing and the MOEX stock price tends to be decreasing in the next period. Thus, the traditional error correction model ($d = 0$) is encompassed in the fractionally integrated error correction model. By expanding the operator $(1-L)^d$ n the x_t term, the fractionally integrated error correction model, following Granger (1986), considers the whole history of the difference, whereas the error correction model indicates that only the most recent price difference is a relevant information variable.

Following Ball and Torous (1983), Kon (1984), Haas et al. (2009), and Chung (2009), a 2-dimensional random vectors, $e_t = (\varepsilon_{Kt}\ \varepsilon_{Rt})'$, is said to have a 2-component multi-variate finite normal mixture distribution, $e_t\,|\Omega_{t-1} \sim$ MNM $(p_1, p_2; \lambda_1, \lambda_2; H_{1t}, H_{2t})$, if its density is given by $f(e_t) = p_1\eta_1(e_t; \lambda_1, H_{1t}) + p_2\eta_2(e_t; \lambda_2, H_{2t})$, where $[p_1, p_2]$ is the positive mixing law with $p_1 + p_2 = 1$, and the component densities are:

$$\eta_j(e_t;\lambda_j,H_{jt}) = \frac{1}{2\pi}\left|H_{jt}\right|^{-1/2} \exp\left\{-\frac{1}{2}(e_t-\lambda_j)'H_{jt}^{-1}(e_t-\lambda_j)\right\}, \quad j = 1,2 \tag{2}$$

where $\lambda_j = E(e|\Omega_{t-1})$. For simplicity, 2-component finite normal mixtures are assumed for two reasons. One is suggested by Alexander and Lazar (2006) that MNM(K) for $K > 2$ is likely to have serious estimation problems. The other is that intuitively, the MNM(2) specification captures two distinct volatility regimes in the stock prices such as usual market volatility, which occurs most of the time, and extreme market volatility which occurs rarely (Cheung and Chung, 2011) for the inflation.

As in conditional correlation GARCH models, two approaches are developed to specify conditional correlation normal mixture GARCH models. First, Bollerslev (1990) CCC-GARCH models are extended to be a bivariate normal mixture process, denoted by the NM-CCC-GARCH model, which captures the extent of skewness and excess kurtosis, but does not yield the time-varying series properties of the correlations between the KASE and MOEX stock markets as follows;

$$\begin{aligned} H_{j,t} &= \begin{bmatrix} h_{j,K,t}^2 & h_{j,KM,t} \\ h_{j,MK,t} & h_{j,M,t}^2 \end{bmatrix} = \Sigma_{jt}\,\Xi_j\,\Sigma_{jt} \\ &= \begin{bmatrix} h_{j,K,t} & 0 \\ 0 & h_{j,M,t} \end{bmatrix} \begin{bmatrix} 1 & \rho_j \\ \rho_j & 1 \end{bmatrix} \begin{bmatrix} h_{j,K,t} & 0 \\ 0 & h_{j,M,t} \end{bmatrix}, \ j = 1,2 \end{aligned} \tag{3}$$

where the variances $h_{j,K,t}^2$ and $h_{j,M,t}^2$ are assumed to follow univariate GARCH processes, respectively, as in (4), (5), and (6);

$$\begin{aligned} h_{j,K,t}^2 &= \omega_{j,K} + \alpha_{j,K}(|\varepsilon_{K,t-1}| - \tau_{j,K,t-1})^2 \\ &\quad + \beta_{j,K}h_{j,K,t-1}^2 + \pi_{j,M}\varepsilon_{M,t-1}^2 \end{aligned} \tag{4}$$

$$\begin{aligned} h_{j,M,t}^2 &= \omega_{j,M} + \alpha_{j,M}(|\varepsilon_{M,t-1}| - \tau_{j,M}\varepsilon_{M,t-1})^2 \\ &\quad + \beta_{j,M}h_{j,M,t-1}^2 + \pi_{j,K}\varepsilon_{K,t-1}^2 \end{aligned} \tag{5}$$

$$h_{j,K,M,t} = \rho_j\sqrt{h_{j,K,t}^2 h_{j,M,t}^2} \tag{6}$$

where the individual GARCH process is called symmetric if $\tau_j = 0$, but asymmetric if it is not and $\omega_j > 0$, α_j, $\beta_j \geq 0$, $-1 \leq \tau_j \leq 1$, for j=1, 2. It is noteworthy that parameter τ allows volatility to react differently to positive and negative shocks of the same magnitude. Ding et al. (1993) argued that this asymmetry in volatility is also referred to as a leverage effect and its incorporation. The regime specific coefficients of volatility spillover effects ($\pi_{j,M}$ and $\pi_{j,K}$) are, respectively, the lagged squared residuals of the MOEX mean equation in explaining the volatility of KASE stock prices, and those of the KASE mean equation in explaining the volatility of MOEX stock prices.

Second, to capture the skewness and kurtosis detected in both conditional and unconditional return distributions, the conventional DCC-GARCH specification originally suggested by Engle (2002) is extended to be a bivariate normal mixture process, denoted by the NM-DCC-GARCH model, which is defined as;

$$H_{jt} = \Sigma_{jt}\,\Xi_{jt}\,\Sigma_{jt},\ j = 1, 2 \tag{7}$$

where $\Xi_{jt} = \begin{bmatrix} \sqrt{g_{j,KK,t}} & 0 \\ 0 & \sqrt{g_{j,MM,t}} \end{bmatrix}^{-1} G_{jt} \begin{bmatrix} \sqrt{g_{j,KK,t}} & 0 \\ 0 & \sqrt{g_{j,MM,t}} \end{bmatrix}^{-1}$, where the 2 × 2 symmetric positive definite matrix $G_{jt} = [g_{j,uv,t}]$ for u, $v = K, M$ is given by:

$$G_{jt} = (1-\delta_{j,1}-\delta_{j,2})\bar{G}_j + \delta_{j_1}\xi_{j,t-1}\xi'_{j,t-1} + \delta_{j_2}G_{j,t-1} \quad (8)$$

with $\xi_{j,t}$ = $\varepsilon_{j,ut}/h_{j,ut}$ for u = K, M and $\bar{Q}_j$ are 2 × 2 unconditional variance matrices of $\xi_{j,t}$.

Suppose that $\{y_t\}$, t = 1, …, T, are generated by the equations (1)–(8) for estimation purposes. Denoting is the row vector of all parameters in the mean and $\upsilon = (p; \lambda; k_1, k_2)'$, where $p = (p_1, p_2)'$, $\lambda = (\lambda_1, \lambda_2)'$, and k_j' is the row vector containing all the parameters in the conditional variance, i.e., $k_j' = (\omega_{j,u}, \alpha_{j,u}, \beta_{j,u}, \tau_{j,u}, \pi_{j,u}, \rho_{j,u}, \delta_{j1}, \delta_{j2})'$, u = K, M, j = 1, 2. Assuming that $\psi_0 = (\varphi_0, \upsilon_0')'$ is the true value of ψ, the approximate maximum likelihood estimator (MLE) maximizes the conditional log-likelihood, $L(\psi_0) = \sum_{t=1}^{T} l_t(\psi_0)$, which is given by:

$$l_t(\psi_0) = ln(\textstyle\sum_{j=1}^{k} p_j\eta_j) \quad (9)$$

where k = 2, $\eta_j = 2\pi^{-1}|H_j|^{-1/2}\exp\left\{-\frac{1}{2}(\varepsilon_t-\lambda_j)'H_j^{-1}(\varepsilon_t-\lambda_j)\right\}$ in equation (1) and p_j for j = 1, 2 are the component densities and the mixing parameter, respectively.

3. Data Description

In this section, the time series characteristics of the data used in the estimation and our methodology are described. Our data set consists of 3414 daily observations of the Kazakhstan and Russia stock prices, and world oil prices, covering the period from 1 June 2006 through 1 March 2021, and are all from the FRED at the Federal Reserve Bank of St. Louise.

The summary statistics are examined for the level and return series of the KASE, MOEX, and WTI, respectively. It is evident that for the skewness, the series is not symmetric except for the return of WTI and the dispersion of a large number of observed values is very high except for the level of WTI, which implies a leptokurtic frequency curve with a high level of risk. This implies that returns do not follow a normal distribution, but exhibit a sharp peak and fat tail distribution. This is confirmed by the Jaque-Bera test for normality. In addition, the Ljung and Box (1976) Q and Q^2 statistics indicate that all return series investigated suffer from long-run dependencies and there is a significant, nonlinear temporal dependence in the squared adjusted returns series, suggesting that the volatility of adjusted returns follows an ARCH-type model. For the unit root tests, this study considers the 4 different unit root tests of the modified rescaled range statistic of Lo (1991), the KPSS statistic of Kwiatkowski et al. (1992), the four different types of Cauchy tests statistics (S_1, S_2, S_3, and S_4) of Bierens and Guo (1993) and Breitung (2002) variance ratio statistic. The nonlinear stationarity tests lead us to the clear conclusion that all variables are nonlinear integrated of order '1', NI(1), although the null hypothesis of stationarity is not rejected for KASE and WTI in Cauchy tests statistics of S_3 and S_4. The estimation results for the summary statistics and unit-roots are available from authors on request but are not reported here for reasons of spaces.

For the cointegration test of KASE and MOEX stock prices, first, the estimated results of Johansen (1988) test shows in Table 1 (A) that the KASE and MOEX are not cointegrated at the 5% level in the case of considering a constant only, but are cointegrated in the case of including both a constant and a trend. Second, as Table 1 (B) illustrates, the test results from Breitung's methodology provide no evidence of cointegration at the 5% level, regardless of whether a constant or a deterministic trend was included in the regression. Third, to examine whether the two market prices are fractionally cointegrated, Geweke and Porter-Hudak (1983) test is considered and their results are reported in Table 1 (C). The results vary little across the different values of μ under consideration. The statistics show that all of the estimates of d are significantly greater than '1', implying that the KASE and MOEX stock prices are nonstationary, but not fractionally cointegrated.

However, to motivate the empirical relevance of fractional integration in mean, the lag 1 through 100 sample autocorrelations are examined for KASE, MOEX, and the residuals from the regression of the KASE stock price on the MOEX stock price. The results are not reported here for reasons of spaces but are available from authors on request. The autocorrelations do clearly exhibit a pattern of slow decay and persistence in all series from the two 95% Bartlett (1946) confidence bands for no serial dependence. In sum, the samples have similar results for the returns of the KASE, MOEX, and WTI in terms of summary statistics and unit root tests. However, they have different implications in the traditional cointegration tests of Johansen (1988) and Breitung (2002), and the fractional cointegration tests of GPH, implying possible fractional and traditional cointegrated relationships between the two markets.

4. Empirical Analysis

This study considers eight models, in which the basic four models include the traditional error correction term in the conditional mean equation, but have different conditional variance and correlation structures with constant correlation coefficients (CCC), dynamic conditional correlation (DCC), normal mixture CCC (NM-CCC) and normal mixture DCC (NM-DCC). The other four models are extensions of the basic model that include the fractionally cointegrated error correction term in the conditional mean equation; that is, FI-CCC, FI-DCC, FI-NM-CCC, and FI-NM-DCC models.

Table 1: Cointegration Tests

<table>
<tr><th colspan="8">Panel A: Johansen's Cointegration Test</th></tr>
<tr><th colspan="2" rowspan="2">Sample</th><th colspan="2">Hypothesis</th><th rowspan="2">λ_{tracex}</th><th>Test Statistics</th><th colspan="2">95% Critical Values</th></tr>
<tr><th>H_0</th><th>H_1</th><th>λ_{max}</th><th>λ_{tracex}</th><th>λ_{max}</th></tr>
<tr><td rowspan="4">KASE and MOEX</td><td rowspan="2">Constant</td><td>$r = 0$</td><td>$r = 1$</td><td>6.52</td><td>6.30</td><td>15.49</td><td>14.26</td></tr>
<tr><td>$r \leq 1$</td><td>$r = 2$</td><td>0.21</td><td>0.21</td><td>3.84</td><td>3.84</td></tr>
<tr><td rowspan="2">Trend</td><td>$r = 0$</td><td>$r = 1$</td><td>19.75</td><td>19.42</td><td>18.39</td><td>17.14</td></tr>
<tr><td>$r \leq 1$</td><td>$r = 2$</td><td>0.33</td><td>0.33</td><td>3.84</td><td>3.84</td></tr>
<tr><th colspan="8">Panel B: Breitung's Cointegration Test</th></tr>
<tr><th colspan="2">Variables and Ranks</th><th colspan="3">Full Sample</th><th colspan="3">95% Critical Values</th></tr>
<tr><th></th><th>Rank r_0</th><th>Λ_q^a</th><th colspan="2">Λ_q^b</th><th>Λ_q^a</th><th colspan="2">Λ_q^b</th></tr>
<tr><td rowspan="2">KASE and MOEX</td><td>0</td><td>70.52</td><td colspan="2">506.98</td><td>329.9</td><td colspan="2">713.3</td></tr>
<tr><td>1</td><td>13.17</td><td colspan="2">55.45</td><td>95.60</td><td colspan="2">281.1</td></tr>
<tr><th colspan="8">Panel C: Fractional Cointegration Test of the residual</th></tr>
<tr><th>Truncation Parameter</th><th colspan="2">$\mu = 0.55$</th><th colspan="2">$\mu = 0.575$</th><th colspan="3">$\mu = 0.60$</th></tr>
<tr><td>Hypothesis</td><td colspan="2">d H_0: d = 1 H_0: d = 0</td><td colspan="2">d H_0:d = 1 H_0:d = 0</td><td colspan="3">d H_0:d = 1 H_0:d = 0</td></tr>
<tr><td>KASE and MOEX</td><td colspan="2">1.19 1.80 11.01</td><td colspan="2">1.15 1.76 12.94</td><td colspan="3">1.10 1.44 14.82</td></tr>
</table>

Note: In Panel (A), r represents the number of cointegrating vectors $\lambda_{max}(r, r + 1) = -T \ln(1-\lambda_{r+1})$ and $\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\lambda_1)$, where λ_i are the estimated eigenvalues. Critical values are from MacKinnon et al. (1999). In Panel (B), the null hypothesis is that the process can be decomposed into a q-dimensional vector of stochastic trend components and a $(n - q)$-dimensional vector of transitory components. The number q of stochastic trend components is related to the cointegration rank r by $q = n - r$. The hypothesis $r = r_0$ is rejected if the test statistic Λ_q exceeds the respective critical value. From Panel (C), the GPH test has a spectral density of $G = (1 - L)^d u_t$ under the null of $I(d = 1)$ against $d < 1$ which is $f_G(\varpi) = |1 - \exp(-i\varpi)|^{-2(d-1)} f_v(\varpi)$, where v_t is a stationary process and $f_v(\varpi)$ is its spectral density. Taking logarithms of a spectral density of $(1 - L)^d u_t$ and evaluating at harmonic frequencies $\varpi_j = 2\pi_j / T$ for j = 0,1,…,T – 1, then we have a simple linear regression equation, $\ln\left[I(\varpi_j)\right] = b_0 + b_1 \ln[4\sin^2(\varpi/2)] + \xi_t$ for j = 1,…,n, where ξ_t is iid and n is an increasing function of T. When the parameters, b, are estimated, the lower truncation parameter was set to $T^{0.1}$, and the upper truncation parameter was set by T^{μ} with μ = 0.55, 0.575, and 0.60. Critical values at the 5% level are –1.84 for μ = 0.55, –1.82 for μ = 0.575, and –1.75 for μ = 0.60.

The parameters are estimated by maximizing the log-likelihood functions in (9) using the CML and MAXLIK procedures in GAUSS.

Table 2 reports the likelihood-based goodness-of-fit measures for the models and their rankings in parenthesis with respect to each of these criteria, i.e., the value of the maximized log-likelihood function, and the AIC and BIC criteria of Akaike (1998) and Schwarz (1978), respectively. In general, the log-likelihood values of the normal mixture GARCH models are quite large compared to those of the usual GARCH models. An astute observer would note that a simple comparison of log-likelihood values is not a rigorous means of selecting a specification from these different models. Because the models under examination are not all properly nested, there is no simple testing procedure to compare their degrees of goodness-of-fit. As a consequence, the normal mixture CCC with the fractionally cointegrated term (FI-NM-CCC) performs best overall according to the criteria. The estimates of the mixing parameters are consistent with the presence of two GARCH processes driving the conditional volatility of the KASE and MOEX stock markets data. The component GARCH process with a larger mixing parameter estimate has a level of persistence, measured by the sum of ARCH and GARCH parameter estimates, that is similar to the level of persistence estimated from the simple GARCH processes. In addition, diagnostic tests on the standardized residuals are also reported in Table 2.

Ljung and Box (1978) statistics for 10th order serial correlation in the residuals and squared residuals suggest that a null hypothesis of autocorrelation and heteroskedasticity

Table 2: Diagnostic Tests on Standardized Residuals

Model	Variables	LLK	AIC	BIC	$\hat{\sigma}^2$	$Q(10)$	$Q^2(10)$	CQ(10)
CCC	$R_{K,t}$	–11727.6 (5)	23497.37 (5)	23626.21 (5)	1.0067	29.11 (0.00)	4.34 (0.93)	24.70 (0.00)
	$R_{M,t}$				1.0033	4.26 (0.93)	8.69 (0.93)	
DCC	$R_{K,t}$	–11698.3 (3)	23440.71 (3)	23575.68 (3)	1.0089	30.22 (0.00)	4.47 (0.92)	65.30 (0.00)
	$R_{M,t}$				1.0028	4.12 (0.94)	8.60 (0.94)	
NM-CCC	$R_{K,t}$	–11400.6 (2)	22871.29 (2)	23086.02 (1)	0.9961	26.38 (0.00)	3.09 (0.97)	22.35 (0.01)
	$R_{M,t}$				1.0041	3.94 (0.94)	11.20 (0.94)	
NM-DCC	$R_{K,t}$	–21401.5 (7)	42802.06 (7)	42802.07 (8)	3.7902	1.24 (0.99)	0.001 (0.99)	0.001 (0.99)
	$R_{M,t}$				3.7452	0.07 (0.99)	0.001 (0.99)	
FI-CCC	$R_{K,t}$	–11731.3 (6)	23506.71 (6)	23641.68 (6)	1.0064	29.66 (0.00)	4.76 (0.90)	24.49 (0.00)
	$R_{M,t}$				1.0032	2.62 (0.98)	8.87 (0.98)	
FI-DCC	$R_{K,t}$	–11703.0 (4)	23452.13 (4)	23593.24 (4)	1.0083	30.71 (0.00)	4.82 (0.90)	64.06 (0.00)
	$R_{M,t}$				1.0028	2.53 (0.99)	8.84 (0.99)	
FI-NM-CCC	$R_{K,t}$	–11397.0 (1)	22866.14 (1)	23087.02 (2)	1.0064	28.00 (0.00)	3.42 (0.96)	22.41 (0.01)
	$R_{M,t}$				1.0053	2.40 (0.99)	11.63 (0.99)	
FI-NM-DCC	$R_{K,t}$	–21401.9 (8)	42802.92 (8)	42802.06 (7)	3.5720	0.12 (0.99)	0.001 (0.99)	0.001 (0.99)
	$R_{M,t}$				5.5126	5.89 (0.82)	0.004 (0.82)	

Note: LLK denotes the value of log-likelihood. The numbers in brackets are the corresponding probabilities. AIC = $-2 \times LLK + 2 \times k$ and SIC = $-2 \times LLK + k \times \log(T)$, where k is the number of estimated parameters from the corresponding models and $T = 3414$. $\hat{\sigma}^2$ denotes the residual variance. The $Q(10)$, $Q^2(10)$, and CQ(10) are the Ljung-Box statistics for tenth-order serial correlation in the residuals, squared residuals, and cross-product of residuals, respectively. The critical value at the 5% significance level is 18.31 for 10 degrees of freedom.

in the standardized residual series should not be rejected. However, for instance, a null hypothesis of heteroskedasticity in the squared residuals should be rejected for NM-CCC, NM-DCC, FI-NM-CCC, and FI-NM-DCC models in the KASE market and NM-CCC, FI-CCC, FI-DCC, and FI-NM-CCC models in the MOEX market.

For dynamics in the conditional means of the KASE and MOEX, Table 3 provides the estimated results of fitting all models. The long memory parameters, d, vary from 0.3911 for the FI-NM-DCC model to 1.2413 for the FI-NM-CCC model, and are statistically significant for all models except the FI-NM-DCC model, at the 5% level. This implies that the residual series is nonstationary, but the limiting value of the impulse response function is equal to '0', such that shocks do not have permanent effects. The series is covariance stationery if $d < 0.5$ and invertible if $d > 0.5$. In particular, for $0 < d < 0.5$, the series possesses long memory, in the sense that the autocorrelations are not absolutely summable. For all models, the KASE and MOEX stock prices do exhibit mean reversion by responding positively to lagged MOEX and KASE stock prices, respectively, implying that there are mutual lead and lag effects between the KASE and MOEX. In particular, the coefficients of the KASE lags in the MOEX equations are generally larger in magnitude than the coefficients of the MOEX lags in the KASE equations, implying that KASE stock prices play a leading role in incorporating new information.

The coefficients for the error correction term in Table 3 are negative for the KASE equation and positive for the MOEX equation and are all statistically significant in the KASE equation with the traditional error correction models and the MOEX equation with the FI-CCC and FI-NM-CCC models. The negative coefficient for the error-correction term in the KASE equation indicates that when the KASE stock price is too high relative to the MOEX stock price, the current KASE stock price will be adjusted downward to achieve the long-run equilibrium relationship. On the contrary, the positive coefficient for the error-correction term in the MOEX equation indicates that when the MOEX is too low relative to the KASE, the current MOEX will be adjusted upward to achieve the long-run equilibrium. Additionally, for example in the FI-NM-CCC model, the coefficient of the error correction term in the MOEX equation is larger in magnitude than in the KASE equation, implying that the MOEX stock prices react to information more rapidly and reach equilibrium faster. Now for the empirical results of oil

Table 3: Conditional Mean Estimates for the KASE and MOEX

Type	With Traditional Cointegrated Term				With Fractionally Cointegrated Term			
Models	**CCC**	**DCC**	**NM-CCC**	**NM-DCC**	**FI-CCC**	**FI-DCC**	**FI-NM-CCC**	**FI-NM-DCC**
d	–	–	–	–	1.2397***	1.2061***	1.2413***	0.3911
					(0.2940)	(0.3082)	(0.2986)	(0.3215)
φ_{K0}	0.0658***	0.0670***	0.0539**	0.0519***	0.0677***	0.0681***	0.0563***	0.0497***
	(0.0205)	(0.0204)	(0.0215)	(0.0174)	(0.0208)	(0.0207)	(0.0214)	(0.0173)
φ_{K1}	–0.0509***	–0.0603***	–0.0531***	–0.0559***	–0.0534***	–0.0615***	–0.0539***	–0.0506***
	(0.0182)	(0.0183)	(0.0166)	(0.0164)	(0.0183)	(0.0184)	(0.0167)	(0.0169)
φ_{M1}	0.0472***	0.0512***	0.0552***	0.0612***	0.0502***	0.0536***	0.0571***	0.0579***
	(0.0143)	(0.0144)	(0.0143)	(0.0144)	(0.0146)	(0.0147)	(0.0144)	(0.0145)
θ_{K1}	0.0486***	0.0468***	0.0477***	0.0502***	0.0466***	0.0450***	0.0475***	0.0496***
	(0.0078)	(0.0079)	(0.0069)	(0.0069)	(0.0077)	(0.0078)	(0.0068)	(0.0069)
γ_K	–0.2711***	–0.2629***	–0.1609***	–0.0382	–2.2998*	–1.8894	–1.6910	0.4688
	(0.0532)	(0.0533)	(0.0591)	(0.0607)	(1.2353)	(1.3252)	(1.1926)	(0.8643)
φ_{M0}	0.0330	0.0341*	0.0370**	0.0534***	0.0271	0.0293	0.0320	0.0442**
	(0.0206)	(0.0207)	(0.0209)	(0.0193)	(0.0203)	(0.0204)	(0.0205)	(0.0189)
φ_{M1}	–0.0241	–0.0252	–0.0249	–0.0347**	–0.0297	–0.0307*	–0.0322*	–0.0248
	(0.0183)	(0.0183)	(0.0170)	(0.0173)	(0.0185)	(0.0185)	(0.0171)	(0.0171)
φ_{K1}	0.1547***	0.1528***	0.1304***	0.1254***	0.1562***	0.1541***	0.1343***	0.1325***
	(0.0153)	(0.0154)	(0.0151)	(0.0150)	(0.0153)	(0.0153)	(0.0150)	(0.0148)
θ_{M1}	0.1159***	0.1146***	0.1090***	0.1124***	0.1169***	0.1158***	0.1101***	0.1118***
	(0.0077)	(0.0077)	(0.0076)	(0.0078)	(0.0077)	(0.0077)	(0.0077)	(0.0078)
γ_M	0.0785	0.1000	0.0841	0.1823***	3.7797**	3.7748**	4.2685***	0.4954
	(0.0659)	(0.0662)	(0.0626)	(0.0633)	(1.4847)	(1.5008)	(1.3757)	(0.8914)

Note: The numbers in parentheses are the corresponding standard errors. ***, ** and * indicates significant at 1%, 5% and 10% level of significance based on *t*-statistics, respectively.

price on the changes in stock returns, the KASE and MOEX stock returns do exhibit mean reversion by responding positively to the lagged WTI prices. Of particular interest are that the coefficients in the MOEX equations are generally larger in magnitude than the ones in the KASE equations, implying that WTI prices play a leading role in incorporating new information in the Russian stock markets.

For time-varying dynamics in the conditional variances and correlations, Tables 4 and 5 present the results of fitting asymmetric conditional variance models to the KASE and MOEX stock markets data. The GARCH parameters in the conditional variance equation are significant at the 5% level for all models. Note that the two versions of bivariate normal mixture GARCH models have two components, that is, $k = 2$ and the off-diagonal elements of β_i are set to zero. Alexander and Lazar (2006) and others found that substantial estimation biases appear when $k > 2$ and allowing for non-zero off-diagonal elements in β_i does not improve the empirical performance of the mixed normal GARCH models they considered. When discussing the parameter estimates from normal mixture GARCH models, the components of the mixture distributions are identified with distinctly different volatility dynamics. For example, the first higher long-term volatility component with the lower mixing weight is stationary in the sense that $\alpha_{i,j} + \beta_{i,j} < 1$ for $i = C$, P and $j = 1, 2$, implying that it has less weight on the reaction parameters in and more weight on the persistence parameters in $\beta_{i,j}$, relative to the second lower volatility component. In particular, the first component in all normal mixture GARCH models is nonstationary, implying that the high volatility component reacts more strongly to shocks, but has a shorter memory. In all cases, the lower (higher) long-term volatility component has the higher (lower) value for the mixing parameter. Thus, the model embeds two different

Table 4: Conditional Variance Estimates for the KASE

Type	With Traditional Cointegrated Term				With Fractionally Cointegrated Term			
Models	**CCC**	**DCC**	**NM-CCC**	**NM-DCC**	**FI-CCC**	**FI-DCC**	**FI-NM-CCC**	**FI-NM-DCC**
ω_{K1}	0.0200***	0.0193***	0.0117***	0.3216***	0.0215***	0.0207***	0.0705	0.4258**
	(0.0029)	(0.0028)	(0.0033)	(0.2816)	(0.0031)	(0.0030)	(0.0607)	(0.2136)
ω_{K2}	–	–	0.0666	0.0096***	–	–	0.0126***	0.0120***
			(0.0603)	(0.0026)			(0.0034)	(0.0031)
α_{K1}	0.0917	0.0907***	0.0536***	0.3925**	0.0915***	0.0907***	0.3420***	0.5943**
	(0048)	(0.0047)	(0.0066)	(0.1953)	(0.0047)	(0.0046)	(0.0953)	(0.2674)
α_{K2}	–	–	0.3533***	0.0467***	–	–	0.0561***	0.0580***
			(0.0996)	(0.0052)			(0.0068)	(0.0064)
β_{K1}	0.9024***	0.9035***	0.8926***	0.8479***	0.9036***	0.9045***	0.8998***	0.7816***
	(0.0040)	(0.0039)	(0.0110)	(0.0856)	(0.0038)	(0.0037)	(0.0206)	(0.0856)
β_{K2}	–	–	0.8952***	0.9138***	–	–	0.8893***	0.8982***
			(0.0211)	(0.0079)			(0.0111)	(0.0092)
τ_{K1}	0.1909***	0.1861***	0.0333	0.1262	0.1752***	0.1727***	0.3551***	0.1616
	(0.0258)	(0.0256)	(0.0472)	(0.2400)	(0.0253)	(0.0251)	(0.1367)	(0.2335)
τ_{K2}	–	–	0.3513**	0.0026	–	–	–0.0085	0.0013
			(0.1366)	(0.0441)			(0.0467)	(0.0425)
π_{M1}	–0.0020	–0.0022	0.0077**	0.1790	0.0007	0.0009	0.0041	0.3789
	(0.0018)	(0.0018)	(0.0029)	(0.1729)	(0.0017)	(0.0017)	(0.0302)	(0.3241)
π_{M2}	–	–	–0.0147	0.0063***	–	–	0.0075***	0.0065**
			(0.0344)	(0.0023)			(0.0029)	(0.0026)
δ_{11}	–	0.0075***	–	0.0805	–	0.0070**	–	0.1063
		(0.0029)		(0.1378)		(0.0028)		(0.1651)
δ_{12}	–	0.9876***	–	0.2061	–	0.9885***	–	0.0937
		(0.0057)		(0.8566)		(0.0054)		(0.6334)
ρ_1	0.1704***	–	0.1545***	–	0.1707***	–	0.2323***	–
	(0.0167)		(0.0226)		(0.0167)		(0.0785)	
P_1	–	–	0.8629***	0.0874***	–	–	0.1326***	0.0857***
			(0.0156)	(0.0113)			(0.0149)	(0.0110)

Note: The numbers in parentheses are the corresponding standard errors. ***, ** and * indicates significant at 1%, 5% and 10% level of significance based on *t*-statistics, respectively.

regimes in stock returns volatility; one is usual volatility, which occurs most of the time, and the other is extreme volatility, which occurs rarely, but which is higher than the usual one. Therefore, the statistically significant estimated mixing weights imply the frequencies with which these two states occurred during the sample period.

Additionally, the estimated results for the traditional CCC and DCC models provide the existence of conditional heteroskedasticity for both the KASE and MOEX stock prices. There is strong persistence in the variance movement and as expected, the two series are highly correlated based on the coefficient, ρ_j, implying that we need to include dynamic conditional correlation in the conditional variance specifications. The estimation results show that the correlation coefficients δ_{1j} and δ_{2j}, for j = 1, 2, are all positive and statistically significant except for the normal mixture models.

One of the main findings of this paper is that the volatility spillover between the two markets is all found to be

Table 5: Conditional Variance Estimates for the MOEX

Type	With Traditional Cointegrated Term				With Fractionally Cointegrated Term			
Models	**CCC**	**DCC**	**NM-CCC**	**NM-DCC**	**FI-CCC**	**FI-DCC**	**FI-NM-CCC**	**FI-NM-DCC**
ω_{M1}	0.0319***	0.0305***	0.0099***	0.1157***	0.0319***	0.0304***	0.4604***	0.1399
	(0.0047)	(0.0045)	(0.0030)	(0.1098)	(0.0047)	(0.0045)	(0.1517)	(0.1225)
ω_{M2}	–	–	0.4474***	0.0152***	–	–	0.0099***	0.0123***
			(0.1494)	(0.0036)			(0.0031)	(0.0033)
α_{M1}	0.0658***	0.0649***	0.0417***	0.3586	0.0677***	0.0673***	0.2503	0.4451
	(0.0079)	(0.0077)	(0.0062)	(0.2787)	(0.0077)	(0.0076)	(0.6581)	(0.3333)
α_{M2}	–	–	0.2765	0.0465***	–	–	0.0431***	0.0447***
			(0.2499)	(0.0071)			(0.0061)	(0.0064)
β_{M1}	0.8880***	0.8901***	0.9335***	0.7888***	0.8870***	0.8888***	0.5270***	0.7745***
	(0.0038)	(0.0085)	(0.0074)	(0.0930)	(0.0087)	(0.0085)	(0.0914)	(0.1003)
β_{M2}	–	–	0.5387***	0.9234***	–	–	0.9328***	0.9295***
			(0.0931)	(0.0086)			(0.0074)	(0.0079)
τ_{M1}	0.3210***	0.3218***	0.1651**	0.2097	0.3067***	0.3025***	–0.9224	0.2215
	(0.0585)	(0.0586)	(0.0721)	(0.3573)	(0.0559)	(0.0554)	(2.4698)	(0.3189)
τ_{M2}	–	–	0.7818	0.1766***	–	–	0.1464**	0.1128
			(0.7272)	(0.0684)			(0.0683)	(0.0658)
π_{K1}	0.0227***	–0.0224***	0.0029*	0.2533**	0.0226***	0.0223***	0.4489***	0.2020***
	(0.0020)	(0.0020)	(0.0017)	(0.0984)	(0.0020)	(0.0020)	(0.1089)	(0.0768)
π_{K2}	–	–	0.4280***	0.0039**	–	–	0.0026	0.0034
			(0.1034)	(0.0019)			(0.0017)	(0.0018)
δ_{21}	–	–	–	0.0008	–	–	–	0.0010
				(0.0163)				(0.0168)
δ_{22}	–	–	–	0.5581	–	–	–	0.4007
				(130.8943)				(12.9078)
ρ_2	–	–	0.2346***	–	–	–	0.1551***	–
			(0.0771)				(0.0224)	
ρ_2	-	-	0.1371	0.9126	–	–	0.8674	0.9143
λ_1	–	–	–0.0138	0.1330	–	–	0.0954	0.0398
			(0.0211)	(0.0814)			(0.1366)	(0.0844)
λ_2	–	–	0.0352*	–0.0120	–	–	–0.2279*	–0.1063
			(0.0193)	(0.0932)			(0.1238)	(0.1651)

Note: The numbers in parentheses are the corresponding standard errors. ***, ** and * indicates significant at 1%, 5% and 10% level of significance based on *t*-statistics, respectively.

significant for the traditional GARCH models and depends on what regime it is in for the normal mixture GARCH models. In the case of the traditional CCC and DCC models in Tables 4 and 5, the parameter estimates (π_M) of the MOEX spillover into KASE vary from –0.0022 for DCC to 0.0009 for FI-DCC, while the parameter estimates (π_K) of the KASE spillover into MOEX vary from –0.0224 for DCC to 0.0227 for CCC. All parameter estimates are statistically significant at the 5% level, implying that there are bidirectional volatility spillovers between both markets. However, the magnitudes of the estimated spillover coefficients from KASE to MOEX are all greater than the other way, implying that the

Kazakhstan stock market informationally leads the Russian stock market. For the normal mixture models, we find that specific patterns for the volatility spillover effect between the two markets is difficult to find, and is analyzed below, focusing on the best model in this study, the FI-NM-CCC model. The coefficients of the volatility spillovers from the MOEX to the KASE are statistically significant at the 5% level in the first, but not the second component, whereas the parameter estimates of the KASE spillover into the MOEX are significant at the 5% level in the second component.

The asymmetric response of volatility to positive and negative shocks is well known in the finance literature as the leverage effect followed by Black (1976), which states that market returns are negatively correlated with changes in return volatility, that is, volatility tends to rise in response to bad news (excess returns lower than expected) and fall in response to good news (excess returns higher than expected) (Nelson, 1991). For the FI-NM-CCC model, a leverage effect seems to be significantly present and positive in the first component of the KASE and MOEX markets, indicating a very strong negative relationship between current returns and future volatility.

Figure 1 depicts the time-varying correlations estimated from the selected NM-DCC models. The figures for the other models including symmetric specifications are not reported for reasons of brevity but are available from the authors upon request. For example, the asymmetric correlation in CCC models is constant (0.1704 for CCC and 0.1707 for FI-CCC) and the asymmetric normal mixture models have constant correlation estimates for regime 1 (0.1545 for NM-CCC and 0.2323 for FI-NM-CCC) and regime 2 (0.2346 for NM-CCC and 0.1551 for FI-NM-CCC). In this regard, Figure 1 displays the component-specific conditional correlations implied by the symmetric NM-DCC and asymmetric FI-NM-DCC models. The upper left panel shows the conditional correlations in the low-volatility component of the symmetric NM-DCC model, while those in the high-volatility component are depicted in the upper right panel. The lower left panel shows the conditional correlations in the low-volatility component of the asymmetric FI-NM-DCC model, while those in the high-volatility component are depicted in the lower right panel. Typically, the correlation coefficient in the low volatility regime is considerably smaller than that in the high volatility regime. These regime-dependent would be seen as very contrasting to the time-varying correlations from the traditional DCC models, which are completely different from those of the CCC models. An important and relevant issue for this study is whether there are striking differences between the regime-specific and regime-dependent correlation coefficients.

5. Conclusion

In this study, we have generalized the univariate mixed normal GARCH model to two versions of the bivariate normal

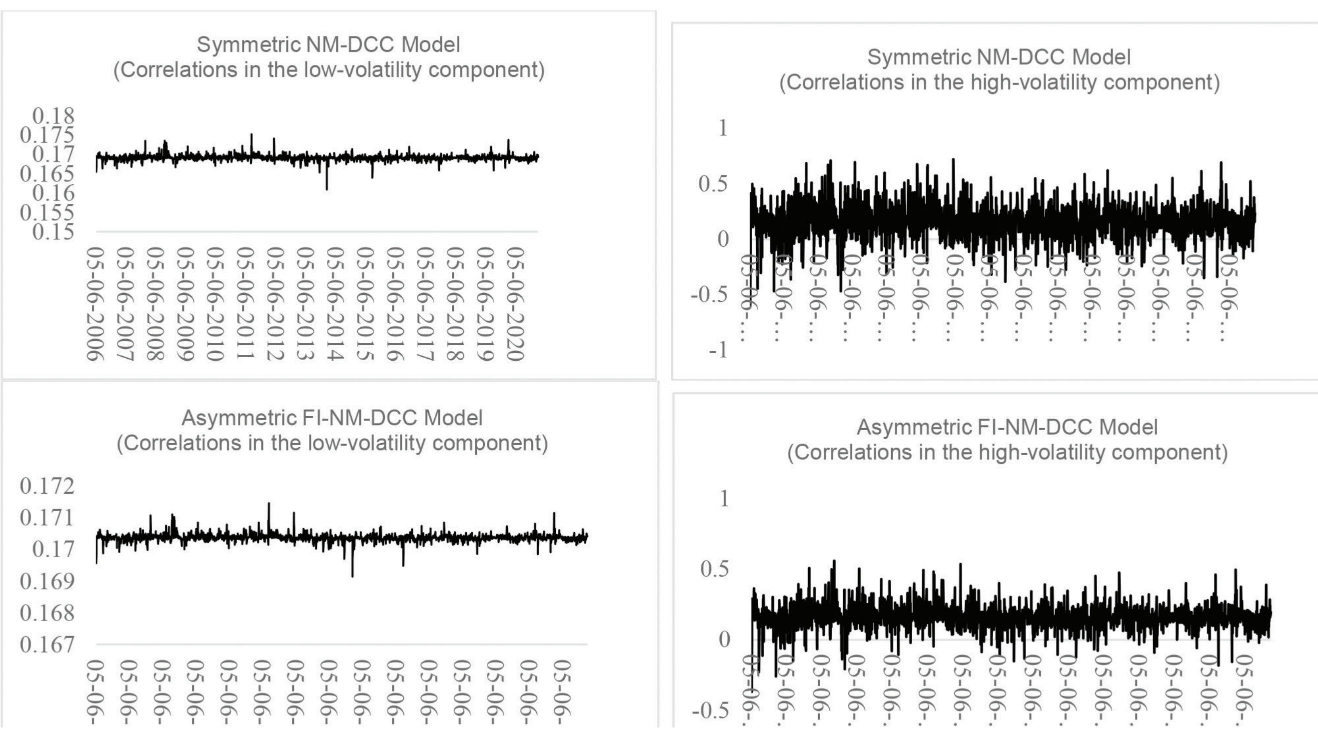

Figure 1: Time-Varying Correlations for the Selected NM-DCC Models

mixture CCC and DCC GARCH models. An application to daily stock prices in the Kazakhstan and Russia stock markets shows that the model captures interesting and relevant properties of the bivariate volatility process, such as regime-dependent leverage effects and conditional correlations.

Our findings are in order. First, for all models, a bidirectional causal relationship between the KASE and MOEX prevails for the traditional error correction models, implying that both KASE and MOEX stock prices can be important sources of information and, additionally, that KASE prices tend to reflect new information more rapidly than MOEX prices. Second, the coefficients for the error correction term are all statistically significant in the KASE equation with the traditional error correction models and the MOEX equation with the FI-CCC and FI-NM-CCC models. Of particular interest are the signs of the estimates for the error correction term, which are all negative for the KASE return equation and all positive for the MOEX return, indicating that the current KASE stock prices will be adjusted downward and the current MOEX stock prices will be adjusted upward to meet the long-run equilibrium. The speed of adjustment is stronger in the Kazakhstan stock market than in the Russian stock market. Third, the KASE and MOEX stock prices do exhibit mean reversion by responding positively to the lagged WTI prices, and the coefficients in the MOEX equations are generally larger in magnitude than the ones in the KASE equations, implying that WTI prices play a leading role in incorporating new information in the Russian stock markets. Fourth, in the case of traditional CCC and DCC GARCH models, there are bidirectional volatility spillovers between both markets and the direction of the information flow seems to be stronger from MOEX to KASE.

For the normal mixture models, i.e. FI-NM-CCC model is the best model in this study, the coefficients of the volatility spillovers between the KASE and the MOEX stock markets are both significant at the 5% level in the second component only. For the asymmetric normal mixture models, the coefficients of the volatility spillovers from the MOEX to the KASE are statistically significant at the 5% level in the first, but not second components, whereas the parameter estimates of the KASE spillover into the MOEX are significant at the 5% level in both the first and second components. Fifth, for the FI-NM-CCC model, the leverage parameters are regime-dependent and are, for example, significantly present and positive in the first component of the KASE and MOEX markets, implying that there is a very strong negative relationship between current returns and future volatility.

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