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LONG MEMORY AND VOLATILITY IN THE BRIC COUNTRIES' STOCK MARKET RETURN[1]

BRIC ÜLKELERİ HİSSE SENEDİ PİYASALARINDA UZUN HAFIZA VE VOLATİLİTE

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ARTICLE INFO	ABSTRACT
Received 25.08.2023 **Revized** 18.09.2023 **Accepted** 25.10.2023 **Article Classification:** Research Article **JEL Codes** A10 C10 C20	In this study, the existence of long memory effect in IBOVESPA, RTSI, S&P BSE, and SSE COMPOSITE stock market indexes of BRIC countries and the long memory volatility in the series were investigated by using, one of the discrete – time models, fractionally integrated ARFIMA and FIGARCH models. For this purpose, daily closing data for the period of 01.07.1997- 30.09.2014 are included in the model. The stationary behavior of IBOVESPA, RTSI, S&P BSE, and SSE COMPOSITE stock market indexes are tested by using ADF, Phillips Perron, and KPSS unit root tests. As a result of classical unit root tests, IBOVESPA, RTSI, S&P BSE, and SSE COMPOSITE stock market indexes are found stationary in I(0). The long memory feature in the series is investigated by using the ARFIMA model, and the long run volatility of the series is researched by using FIGARCH model. According to the result of ARFIMA model, RTSI, S&P BSE and SSE COMPOSITE series have a stationary long memory, and only the SSE COMPOSITE stock market index parameter is statistically significant in FIGARCH model. Thus, the long memory behavior of the SSE Composite stock index displays predictable behavior. **Keywords:** BRIC Countries Stock Market, Long Memory, Volatility, ARFIMA, FIGARCH

MAKALE BİLGİSİ	ÖZ
Gönderilme Tarihi 25.08.2023 **Revizyon Tarihi** 18.09.2023 **Kabul Tarihi** 25.10.2023 **Makale Kategorisi** Araştırma Makalesi **JEL Kodları** A10 C10 C20	Bu çalışmada, BRIC ülkelerine ait Bombay Menkul Kıymetler Borsası (S&P BSE), Bovespa (IBOVESPA), Rusya Ticaret Sistemi (RTSI), ve Şangay Kompozite (SSE COMPOSITE) endekslerinde uzun hafıza etkisinin varlığı ve serideki uzun hafıza oynaklığı, kesikli bütünleşik zaman serisi modellerinden olan "Otoregresif Kesirli Bütünleşik Hareketli Ortalama (ARFIMA)" ve "Kesirli Bütünleşik Genelleştirilmiş Otoregresif Koşullu Değişen Varyans (FIGARCH)" modelleriyle incelenmiştir. Bu amaçla çalışmaya 01.07.1997-30.09.2014 dönemine ait günlük kapanış verileri modele dahil edilmiştir. IBOVESPA, RTSI, S&P BSE ve SSE COMPOSITE borsa endekslerinin durağanlık davranışları ADF, Phillips Perron ve KPSS birim kök testleri kullanılarak test edilmiştir. Klasik birim kök testleri sonucunda IBOVESPA, RTSI, S&P BSE ve SSE COMPOSITE borsa endeksleri I(0) noktasında durağan bulunmuştur. Serilerdeki uzun hafıza özelliği ARFIMA modeli kullanılarak, serilerin uzun dönem oynaklığı ise FIGARCH modeli kullanılarak araştırılmıştır. ARFIMA modelinin sonucuna göre RTSI, S&P BSE ve SSE COMPOSITE serilerinin durağan uzun belleğe sahip olduğu; FIGARCH modelinin sonucuna göre ise sadece SSE COMPOSITE hisse senedi endeksinin uzun hafıza davranışının öngörülebilir olduğu belirlenmiştir. **Anahtar Kelimeler:** BRIC Ülkeleri, Hisse Senedi, Uzun Hafıza, Oynaklık, ARFIMA, FIGARCH

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1. Introduction

Interest in long-term dependence or long memory processes first appeared in physical sciences, and the first study on the subject was made by Hurst (1951), a British hydrologist. In this study, Hurst tried to determine how to set the overflow periods of the Nile river. After that Mandelbrot and Wallis (1968) identified long memory as "Joseph influence". Based on the Joseph's influence, Egypt will have an abundance for seven years and famine for seven years. According to this study, the long memory is a phenomenon of an event in the distant past to be highly correlated with future observations. The effect of the long memory period on the financial markets was revealed by Mandelbrot (1971). In the study, it was suggested that Hurst's "Transformed Width" statistic be used to determine the long memory behavior of stocks. Long memory models are divided into two as discrete and continuous models. The continuous long memory model is described by Mandelbrot (1965) as a "fractional Brownian motion", generalized by Mandelbrot and Van Ness (1968). The discrete long memory model was developed as a fractional autoregressive motion model, ARFIMA (p, d, q), by Granger (1980), Granger, and Joyeux (1980) and Hosking (1981).

In capital markets, it has long been a matter of curiosity for how effective the markets are. In particular, investors want to know how much they will get or how much they will lose when they make investments. This has prompted both academicians and market professionals to investigate these issues. Researchers have found the so-called "volatility" to be able to determine how much of the capital has risen. While the volatility models have been developed for the short memory series before, later they have also been developed for long memory models. FIGARCH model, which detects volatility in long memory series was presented by Baille et al (1996). In recent years, there have been several studies that have demonstrated the use of long memory by using fractionally integrated models.

Doornik and Ooms (2004) compared the methods used for estimating the ARFIMA model with each other. The quarterly UK inflation series for the period 1959.1 - 2002.2 and the monthly inflation series for the United States of America from 1957.1 to 2003.4 were included in the study. Exact Maximum Likelihood, Modified Profile Likelihood (MPL) and Nonlinear Least Squares methods were compared with each other and the MPL method was found to give more accurate results than other methods.

Kang and Yoon (2006) investigated the asymmetric long memory effect of the volatility of stocks in Japan, South Korea, Hong Kong, and Singapore with ARFIMA, FIGARCH, and FIEGARCH models. As a result of the study, the FIEGARCH model proved to be more successful in catching asymmetrical effects in long memory.

Kasman and Torun (2007) investigated a long memory feature of Turkey's stock index in the period of 1988-2007 with fractionally integrated models. As a result of Turkey's stock index was also found to have a long memory both in returns and volatility.

In the study of Leite, Rocha, Silva, et al. (2007), they tried to determine the long-term correlations using circadian rhythm, sleeping in different regimes, walking periods, and increasing age values using DFA combined with segmentation and selective adaptive ARFIMA models. As a result of the study, the selective adaptive ARFIMA model predicted long memory based on shorter segments, therefore, it is more advantageous to use ARFIMA models.

Siew, Chin, and Wee (2008) aimed to demonstrate and exemplify the use of time series models in Air Pollution Index (API) estimates. The data used in the study consist of API observations covering the period of 03.1998 - 12.2003. ARIMA and ARFIMA time series methods were used. As the model selection criterion, the lowest values of MAE, RMSE, and MAPE are taken into consideration. When considering these two models, the integrated ARFIMA model is better because it has the lowest MAPE value.

In the Wiphatthananananthaku and Sriboonchitta (2010), implemented the SET50 index option in conjunction with the Chicago Board Options Exchange (CBOE) in their study as Thailand volatility index. Long memory predicted ARFIMA - FIGARCH and ARMA - FIAPARCH models with the ability to capture the effect of asymmetry in conditional variance and power transfer in the conditional variance of the process. As a result of the study, while ARMA-FIGARCH model is more adaptive, ARMA-FIAPARCH has a longer memory than ARMA-FIGARCH and catches asymmetrical effects better.

In the study of Zhou, Chen, and Dong (2012), they estimate the traffic network in the northeastern part of China was based on the ARFIMA model. The data consist of traffic data for 3 days from 0:00 to 24:00 in October 2009. The MATLAB program was used to analyze the data. According to the findings, the ARFIMA model provides better results than traditional time series methods in the long correlation analysis.

In the study of Guhathakurda, Bhattacharya, and Bhattacharya (2012) used daily returns, absolute returns, and square returns of the stock markets from developed markets (USA, UK, Germany, Australia, New Zealand, Hong Kong, France, Netherlands, Japan, Singapore) and from developing markets (Russia, Hungary, Brazil, Chile, Mexico, Malaysia, Korea, Taiwan, China, and India) investigated the long memory properties of them. Hurst exponent, Lo's statistics, and semi-parametric GPH statistics were calculated to determine the long memory of asset returns. As a result, it has been found that there is volatility in the long memory acquisition both in the developing and developed markets, and there is no significant difference between the long memory statistics of the two market groups.

In Kristoufek (2013) investigated mix-related ARFIMA (MC-ARFIMA) processes, which allowed various properties of univariate and bivariate long memory and found that mix-related ARFIMA processes enhance to create Maximum Likelihood Estimators, Generalized momentum estimators, and Frequency domain estimators.

In the article of Wook Han (2014), it was investigated the effects of the global crises of 1997-1998 and the global crises of 2008 - 2009 on the long memory volatility of exchange rates compared with the parametric FIGARCH model and the semi-parametric Local Whittle method. Daily exchange rates of KRW-USD and JPY-USD are included in the study. As a result of the study, the KRW-USD reflects the long-term volatility dependence more than of JPY-USD and two financial crises affect the dynamics of volatility in all return series.

In the study of Türkyılmaz ve Balıbey (2014), the efficiency of the Pakistani stock index for the period 2010-2013 was estimated by ARFIMA - FIGARCH methods under different distributions (Normal, Student - t, Skewed Student - t and GED distributions). While the ARFIMA model does not reflect long memory behaviors for the Pakistan stock index, it is determined that the volatility of the index return series is long memory as a result of the estimated FIGARCH model.

In this paper, it is investigated that whether the stocks of the BRIC countries, which have the largest land pieces on the map, have strong memory by using the ARFIMA model, and the existence of long memory volatility is determined using the FIGARCH model. In this paper, we applied ARFIMA-FIGARCH models to BRIC countries, due to the long memory is a feature of emerging market stock market indices rather than a feature of developed countries' stock market indices.

The organization of the paper is as follows. Section II introduces employed econometric methodology, Section III reveals data and empirical results and Section IV presents the conclusion of the study.

2. Method

2.1. ARFIMA Method

The concept of fractional integration is the definition of time series, often with a long memory or long-term dependence. Time series with a purely stationary ARIMA process have a short memory. The AR (p) model has infinite memory and all past values of the error term are stored in y_t. However, the effect of these past values follows geometric decline. The MA (q) model has a short memory and the effect of the present value disappears after q delay. In the ARIMA model, the researchers treat "d" as an integer number to make sure that the series formed by taking the difference have a stationary process. However, the ARIMA model becomes fractional when d gets all real numbers and is often referred to as the ARFIMA model (Baum, 2013). The ARFIMA method was developed by Granger (1980), Granger and Joyeux (1980), and Hosking (1981). The mathematical formulation of the method is shown as below.

Classic ARMA process:

$$y_t = \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q}, \qquad (1)$$

$$t = 1,2,\dots,T \qquad \varepsilon_t \sim NID(0, \sigma^2_{\varepsilon}),\ E[\varepsilon_t] = 0,\ E[\varepsilon_t] = \sigma^2_{\varepsilon}.$$

When latency polynomials and μ are written using mean term, the model can be written as equation (2) (Doornik ve Ooms, 2012, s. 5).

$$\phi(L)(y_t - \mu) = \theta(L)\varepsilon_t \qquad (2)$$

ARFIMA (p, d, q) model with d integration level, p autoregressive level and q moving average levels are:

$$\phi(L)(1 - L)^d (y_t - \mu) = \theta(L)\varepsilon_t \qquad (3)$$

Here, d is the difference parameter, ϕ (L) and θ (L) are polynomial roots that all roots are outside the unit circle. Ɛt is the white noise process

$$\phi(L) = 1 - \sum^{p}_{j=1} \phi_j (L)^j \qquad (4)$$

$$\theta(L) = 1 - \sum^{p}_{j=1} \theta_j (L)^j \qquad (5)$$

The binomial expansion of $(1-L)^d$ is as shown below (Balcılar, 2002).

$$(1-L)^d = \sum_{j=-\infty}^{\infty} b_j L^j \tag{6}$$

$$b_j = \frac{\Gamma(j-d)}{\Gamma(j+d)\Gamma(-d)} = \prod_{0<k<j}(k-1-d)/k,\ \text{j= 0,1,2,..} \tag{7}$$

The spectral density f (0) = 0 for the I (d) process and ƒx (ω) = cω-2d for the low frequencies (Granger, 1980). Here, the value of the fractional coefficient "d" is less than zero, which indicates that the series has a weak memory. If "d" is between (0, 1/2), the series has a stationary long memory, and if "d" is between (1/2, ∞) indicates that the series has non-stationary long memory processes (Banerjee ve Urga, 2005, s.14).

2.2. FIGARCH Method

Due to the development in financial markets, the number of investors has been increased in time. This situation has let to the close relationship between financial markets and macroeconomic variables. Thus, to prevent losses and damages that could be caused by high volatility, it is necessity to model the changes observed in prices in financial market. To achieve this, "Fractional Integrated Conditional Variance Models", which incorporate long memory conditions, have started to be applied frequently (Nazarian, Nederi ve Alikhani, 2014, s. 16-17).

FIGARCH (p,d,q) model, which was found by Baille et al. (1996) is defined as:

$$[1-\beta(L)]\,\sigma_t^2 = \omega + [1-\beta(L) - \phi(L)\,(1-L)^d\,]\,\varepsilon_t^2$$

B(L) and ϕ (L) are polynomial roots in the delay operator and d is the long memory parameter; are shown as follows:

$$\phi(L) = (\,1-\alpha(L) - \beta(L))(1-L)^{-d},$$

$$\alpha(L) \equiv \alpha_1 L + \ldots + \alpha_q L^q$$

$$\beta(L) \equiv \beta_1 L + \ldots + \beta_q L^q$$

It is also assumed that all the roots belonging to polynomials ϕ(L) and (1- β (L)) extend outside the unit circle. In ARFIMA class models, while long term dependence of time series is modeled by fractional difference parameter, short term behaviors are captured by traditional ARMA parameters. The same situation holds for the validity of the model of conditional variance. In the covariance stationary GARCH (p, q) model, the optimal estimate of the future conditional variance is decreasing exponentially and it is important for the estimation of the IGARCH (p, q) model. In the FIGARCH (p, d, q) model, a shock effect in the prediction of the future running variance will disappear with a slow hyperbolic rate (Bollerslev ve Mikkelsen, 1996: 158). In the FIGARCH model, when d = 0, the process becomes the standard GARCH (1,1) process, and when d = 1, it becomes the IGARCH (1,1) process. The main point of the FIGARCH algorithm is to allow the autocorrelation of absolute values and squares to decrease in slow hyperbolic order when $0 \le d \le 1$ (Wook Han, 2014).

3. Data Set and Empirical Results

3.1. Data Set

To investigate the long memory effect and the long-term volatility of the return series of BRIC countries' stock market indexes; RTSI for Russia, SSE COMPOSITE for China, S&P BSE for India, and

IBOVESPA index for Brazil were examined. All data belonging to the series were obtained from the "finans.yahoo.com" website and daily closing values covering the period 01.07.1997 - 30.09.2014 were used.

To be able to perform the analysis, the daily sample prices are converted to the daily nominal return series by using the formula as shown below:

$$r_t = 100 \ln (P_t/P_{t-1}), \qquad t = 1,....,T.$$

In the formula, rt is the rate of return at time t, P_t is the price of the series at time t, P_{t-1} is theprice of the previous day of the series.

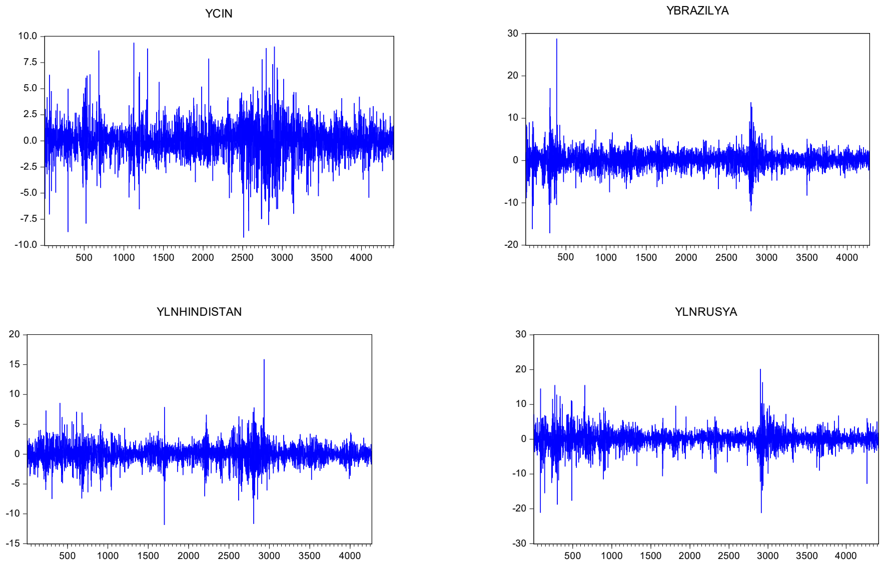

Figure 1. Daily returns of SSE COMPOSITE, IBOVESPA, S&P BSE and RTSI indexes.

As you can see in Figure 1, large changes are followed by large changes, while small changes are followed by small changes in the series. Also, it appears that the two major financial crises experienced seriously affected the series. The first of them is the Asian Crisis. The Asian crisis began with the serious depreciation of the Thai currency in early July 1997 and the effects were seen for a long time. This situation mostly affected Asian countries. As seen in the yield graphs, among the BRIC countries, China was the most affected country during that period. The second of them is the Global Crisis. The global crisis started to show its effect in March 2007, and in September 2008 the crisis reached its peak. The collapse of the risky mortgage industry in America is the underlying cause of this crisis and almost all the countries of the world are affected by this crisis. Again, as observed in the graphs, the volatility of the stocks of the countries increased in 2008.

Table 1. Descriptive Statistics of SSE COMPOSITE, IBOVESPA, S&P BSE, and RTSI Indexes

Series	SSE COMPOSITE(China)	IBOVESPA(Brazil)	S&P BSE (India)	RTSI (Russia)
N	4406	4277	4268	4414
Average	0.0114459	0.03335	0.042729	0.022093
Median	0	0.080179	0.098388	0.07898
Maksimum	9.400787	28.83245	15.98998	20.20392
Minimum	-9.25615	-17.20824	-11.80918	-21.19942
Standart deviation	1.544692	2.14248	1.62114	2.564148
Skewness	-0.11791	0.336796	-0.09542	-0.485892
Kurtosis	7.700897	16.29452	8.760846	11.46483

Jarque-Bera	4066.191	31570.76	5906.91	13348.91
***p* prob. value**	0.00	0.00	0.00	0.00

Table 1 contains descriptive statistics of the return series. According to the obtained descriptive statistical results, the return series show small average values and large standard deviations. The skewness values of the series show negative asymmetry – except Brazil -, and the kurtosis values of the series are greater than 3. Thus, there is a thick tail problem in all of the series, and the series don't fit to the normal distribution. To understand whether the series exhibit the normal distribution, the Jarque - Bera test is also applied. As a result of the Jarque - Bera test, the zero hypothesis is rejected because the probability value is found less than 0.05. Thus, the series are not normally distributed. Besides, whether the error terms of the series distribute normal are examined and it is found that the error terms are not appropriate for the normal distribution.

3.2. Unit Root Test Results

The stationary behaviors of the series must be investigated before analysis whether the series have a long memory. For this reason, classical unit root tests [ADF (Augmented Dickey-Fuller), PP (Phillips Perron), and KPSS (Kwiatkowski, Phillips, Schmidt, and Shin)] is applied to all sample returns. These tests differ in terms of the null hypothesis. While the null hypothesis of ADF and PP tests is "The time series have unit root", the null hypothesis of the KPSS test is "time series is stationary". The experimental results of classical unit root tests are given in Table 2.

Table 2. Classical Unit Root Test Results

		SSE COMPOSITE(China)	IBOVESPA(Brazil)	S&P BSE (India)	RTSI (Russia)
ADF	**Trend + Constant**	-15.20437	-19.65331	-14.72035	-11.63873
	p value	0.000	0.000	0.000	0.000
	Constant	-15.20177	-19.655	-14.70319	-11.6369
	p value	0.000	0.000	0.000	0.000
	None	-15.19273	-19.6264	-14.60706	-11.63444
	p value	0.000	0.000	0.000	0.000
PP	**Trend + Constant**	-66.09908	-64.25673	-60.71386	-59.05919
	p value	0.000	0.000	0.000	0.000
	Constant	-66.10376	-64.26464	-60.71455	-59.06549
	p value	0.0001	0.0001	0.0001	0.0001
	None	-66.10472	-64.23049	-60.70076	-59.05642
	p value	0.0001	0.0001	0.0001	0.0001
KPSS	**Trend + Constant**				
	LM -STAT	0.083011	0.083422	0.083625	0.168024
	1%	0.216000	0.216000	0.216000	0.216000
	5%	0.146000	0.146000	0.146000	0.146000
	10%	0.119000	0.119000	0.119000	0.119000
	Constant				
	LM -STAT	0.097192	0.088441	0.126369	0.165125
	1%	0.739000	0.739000	0.739000	0.739000
	5%	0.463000	0.463000	0.463000	0.463000
	10%	0.347000	0.347000	0.347000	0.347000

As a result of ADF, PP, and KPSS unit root tests, the series do not show unit root behaviors with the significance levels of 1%, 5%, and 10%. Therefore, the null hypothesis is rejected in the ADF and PP tests and is accepted in the KPSS test. The series are stationary. All series used in the study are suitable for the analysis of long memory models.

3.3. ARFIMA Test Results

The "Approximate Whittle Method" is used when analyzing ARFIMA (p, d, q) series. To find out the best ARFIMA(p,d,q) model, all possible models are tested for $p + q \leq 2$. When the best model is determined, the significance of the parameters and the AIC information criterion are taken into account. The "d" and AIC information criterion values obtained in Table 3 are given.

Table 3. ARFIMA Test Results

Modeller		(0,d,0)	(0,d,1)	(1,d,0)	(1,d,1)	(0,d,2)	(2,d,0)	(2,d,1)	(1,d,2)	(2,d,2)
SSE COM.	d-coefficient	0.0151	0.0329	0.0291	0.0098	0.0771	**0.078**	0.0727	0.0712	0.0465
	p value	0.20212	0.09056	0.11839	0.4553	0.00448	0.0004	0.00442	0.00925	0.00486
	AIC	144.107	144.664	144.93	145.88	136.94	135.015	136.7	137.7964	127.893
	Q(5)	17.4145	16.8925	17.0563	16.881	5.35974	3.47227	3.48557	4.880354	-
	Q(10)	30.9098	31.533	31.426	27.686	23.9354	22.0638	21.4148	22.43315	9.64122
	Q(15)	46.3365	45.5654	45.7315	42.981	35.9621	34.1021	33.6107	34.57738	22.2551
IBOSVEPA	d-coefficient	-0.0076	-0.04584	-0.049	-0.0477	-0.0497	-0.0464	-0.05293	0.00339	-0.05342
	p value	0.52594	0.01248	0.01607	0.0547	0.03768	0.06707	0.01039	0.86187	0.03987
	AIC	2937.46	2931.98	2931.97	2933.9	2933.91	2933.93	2924.35	2938.342	2926.45
	Q(5)	16.4342	4.65703	4.18249	4.3512	4.02569	4.52555	3.45535	19551.75	-
	Q(10)	54.1024	43.7498	43.4417	43.541	43.3069	43.6383	39.0494	36365.11	35699.1
	Q(15)	61.3675	50.570	50.2845	50.371	50.1456	50.455	50.2971	50823.62	49512.3
S&P BSE	d-coefficient	**0.0362**	-0.0221	-0.0216	-0.0084	0.0077	0.012	0.0122	0.0456	0.0161
	p value	0.00256	0.21681	0.29952	0.6635	0.75862	0.61745	0.67482	0.31313	0.36015
	AIC	544.994	530.477	532.572	530.03	528.956	528.626	530.625	530.3258	528.576
	Q(5)	23.7508	5.20062	7.54474	3.5498	3.07677	2.85757	2.86016	3.735355	-
	Q(10)	50.6757	30.8537	33.5805	28.535	27.423	26.8876	26.8816	25.52207	23.721
	Q(15)	61.3547	41.5326	44.2717	39.027	37.8213	37.2628	37.2567	36.23475	33.9029
RTSI	d-coefficient	0.0855	**0.0414**	0.0361	0.0359	0.0305	0.0357	0.0278	0.0273	0.1604
	p value	0.000	0.02112	0.07444	0.1556	0.1869	0.15694	0.22447	0.17606	0.01504
	AIC	4563.53	4555.16	4554.93	4556.9	4556.62	4556.92	4556.8	4555.25	4553.74
	Q(5)	21.077	8.97864	8.18116	8.1584	7.21386	8.13351	4.45902	3.050378	-
	Q(10)	39.5419	26.8746	26.2337	26.217	25.541	26.1994	23.7754	22.5423	24.0822
	Q(15)	59.7941	49.604	49.2084	49.199	48.7591	49.1888	46.8279	45.51328	40.9972

As a result of ARFIMA method, ARFIMA(2, d, 0) model for China, ARFIMA(0, d, 0) model for India, and ARFIMA(0, d, 1) model for Russia are found as suitable models. Those return series have a long memory. For Brazilian stocks, even though the d parameter is in the range of 0 to 0.5, the appropriate model is not found because the d, AR and MA parameters are not significant. Thus, Brazilian stock does not have a long memory. To avoid the autocorrelation problem in the series, the NEW-WEST robust method is applied to the models and the problem is abolished. Also, Ljung-Box statistical values are examined to determine whether error terms have ARCH effects, and $X^2_{(m-k)}$ distribution is used to decide whether the statistic is significant. In the $X^2_{(m-k)}$, k refers to the number of parameters estimated. In table 3, the values for Q(5), Q(10), and Q(15) are given. It is seen that the SSE COMPOSITE stock market doesn't have an ARCH effect in Q(5)'th delay, but it has an ARCH effect in Q(10), Q(15), Q(20). India and Russia are also found to have an ARCH effect for the above 3 delays and more.

3.4. FIGARCH Test Results

In GARCH models, it is necessary to satisfy the conditions for the conditional variance to be positive. For this purpose, while estimating the FIGARCH models, the constraints specified by Condrad and Haad (2006) are used in this study. The results of estimated FIGARCH models is shown in Table 4.

Table 4. Estimated FIGARCH (1,d,1) Model Results of Indexes

	SSE COMPOSITE	S&P BSE	RTSI
M	0.011	0.092	0.082
	(0.017)	(0.024)	(0.034)
Ω	0.283	0.027	0.139
	(0.096)	(0.014)	(0.07)
α1	0.066	-0.225	-0.274
	(0.049)	(0.164)	(0.182)
β1	-0.066	0.729	0.524
	(0.02)	(0.095)	(0.208)
d	0.306	0.573	0.439
	(0.038)	(0.09)	(0.073)

Note: The values in parentheses are the standard errors of the parameters.

According to the results obtained from the FIGARCH test, only the SSE COMPOSITE stock market index provides the necessary constraints from all the series. SSE COMPOSITE index is different from zero with d = 0.306 and is suitable for a long memory. Although S&P BSE and RTSI have a long memory and show ARCH effect, they do not confirm to the long memory volatility model. Based on the obtained resutls, for SSE COMPOSITE index future volatility will depend on past events, and for this reason, future forecasts can be made.

4. Conclusion

In this study, the volatility of stock market indexes of BRIC countries is investigated by using ARFIMA and FIGARCH models. To find out the fractional behavior of the series, data covering the period 01.07.1997 - 30.09.2014 is included in the study. Firstly, classical unit root tests are applied to determine the stationary behavior of the series. As a result of ADF, Phillips Perron, and KPSS unit root tests, the series are found stationary at I(0) level. Secondly, to investigate whether the series have a long memory, the ARFIMA model is applied to the series separately. As a result of the ARFIMA model estimated by using the Whittle method, it is found that the RTSI, SSE COMPOSITE, and S&P BSE indexes have a stationary long memory feature with the exception of the Brazilian IBOVESPA index. Lastly, the FIGARCH model is used in the modeling of volatility. According to the obtained result, only the Chinese's SSE COMPOSITE index provides a long memory volatility. These findings reveal that the long memory behavior of the return series indicates that stock prices display predictable behavior.

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