Cilt: 11 • Özel Sayı • 2011
ss. 19-28

Analyzing the Dual Long Memory in Stock Market Returns

Borsa Endeks Getirilerinde İkili Uzun Hafıza Analizi

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ABSTRACT

The purpose of this study is to examine the dual long memory properties for five stock market returns by using joint ARFIMA-FIGARCH model and structural break test in context of weak form efficient market hypothesis. The models are estimated by using daily closing prices for S&P500, FTSE100, DAX, CAC40 and ISE100. In an effort to assess the impact of structural breaks in volatility persistence, the breaks in variance are detected by using the Iterated Cumulative Sums of Squares (ICSS) algorithm, and dummy variables are incorporated to the models. Empirical findings show that the dual long memory exists for all stock markets. Also the volatility has a predictable structure and indicates that all stock markets are weak form inefficient. Further, it is found that incorporating information on structural breaks in variance improves the accuracy of estimating volatility dynamics and effectively reduces the persistence of volatility.

Keywords: Long memory, ARFIMA-FIGARCH, structural break, ICSS, stock return volatility, volatility shifts, volatility persistence

ÖZET

Bu çalışmanın amacı, zayıf formda etkin piyasa hipotezi bağlamında birleşik ARFIMA-FIGARCH modeli ve yapısal kırılma testi kullanarak beş farklı borsa endeks getiri serisi için ikili uzun hafıza özelliklerini incelemektir. Modeller S&P500, FTSE100, DAX, CAC40 ve ISE100 borsa endekslerinin günlük kapanış fiyatları kullanılarak test edilmiştir. Volatilite sürekliliği üzerinde yapısal kırılmaların etkilerini belirlemek üzere ICSS (Iterative Cumulative Sums of Squares) algoritması ile varyanstaki kırılmalar tespit edilmiş ve modellere kukla değişkenler olarak eklenmiştir. Analiz sonuçlarına göre, tüm borsalar için ikili uzun hafızanın bulunduğu anlaşılmıştır. Ayrıca volatilitenin öngörülebilir yapı göstermesi nedeniyle tüm borsaların zayıf formda etkinsiz oldukları sonucuna varılmıştır. Bunun yanı sıra, varyanstaki yapısal kırılmaların modellere eklenmesiyle volatilite dinamiklerinin daha doğru hesaplandığı ve volatilite sürekliliğinin fiilen azaldığı saptanmıştır.

Anahtar Kelimeler: Uzun hafıza, ARFIMA-FIGARCH, yapısal kırılma, ICSS , getiri volatilitesi, volatilite kaymaları, volatilite sürekliliği

1. INTRODUCTION

Efficient market hypothesis (EMH) proposed by Fama (1970) has had a great influence in theoretical and empirical finance. The EMH is based on whether newly generated information is instantaneously and sufficiently reflected in stock prices. Based on the point of time of generation, information which are used in developing investment strategies can be classified into three types as: historical information, public information, and future (or internal) information. Additionally, depending on the reflection of information in stock prices, the EMH can be classified again into three types as: weak-form EMH of historical information, semi strong-form EMH of public information and strong-form EMH of future information. EMH states that, the weak form efficiency exists if stock prices fully reflect all the information contained in the history of past prices and movement. If capital markets are weak form efficient, then investors cannot earn excess profits from trading rules based on past prices or returns. Therefore, stock returns are not predictable, and so-called technical analysis is useless (Eoma et al., 2008 and Mun et al., 2008).

Long memory dynamics are important indicators for detecting non-linear dependence in the conditional mean and variance of financial return series. Because, long memory in returns affects the efficiency of the market in pricing securities. The presence of long memory in asset returns means that the market does not immediately respond to information flows into the financial markets, but reacts to it progressively over time. If asset returns display long memory, or long-term dependence, then the observations have a predictable component and therefo-

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re, past asset returns could be used to predict future returns and the possibility of consistent speculative profits may arise, contradicting the weak form EMH. Long memory in volatility, however, shows that uncertainty or risk is an important determinant of the behavior of stock prices (Kasman and Torun, 2007, Kasman et al., 2009, Barkoulas et al., 2000). Hence, modeling long memory properties in returns and volatility has become an appealing research issue in finance. In recent studies, much of the empirical work suggests that return series are fractionally integrated with a differencing parameter that is significantly different from zero and unity. The ARFIMA-FIGARCH model has a distinctive feature. It allows us to estimate the degree of persistence in both returns and uncertainty (volatility) simultaneously.

This paper mainly focuses on the dual long memory dynamics across the stock returns for four developed markets (financial centers) and an emerging market. The reason why these countries have been chosen is to reveal the applicability of the joint ARFIMA-FIGARCH model and the disparity of unpredictable market response to information flow with the results of the analysis. Since some studies argued that sudden changes or structural breaks may give rise to spurious long memory in conditional variance, breaks in variance are detected by using ICSS algorithm and introduced to the model by dummy variables. The paper also sheds light on the current issue of the relationship between returns and uncertainty.

The rest of the paper is organized as follows: Section 2 presents review of the literature, while Section 3 discusses the joint ARFIMA–FIGARCH model, and ICSS algorithm. The statistical characteristics of sample data, empirical results of unit root and long memory tests, and models estimations are summarized in Section 4. The final section, provides concluding remarks.

2. LITERATURE REVIEW

Literature on long memory in the conditional mean and variance had evolved independent of each other, as the phenomena appear distinct. However, long memory phenomena are often observed in both the conditional mean and variance at the same time. Based on this idea, the empirical studies have focused on the dual long memory property in the conditional mean and conditional variance (Kang and Yoon, 2007:591).

Kasman et al. (2009) investigate the presence of long memory in the eight Central and Eastern European countries' stock markets by using the ARFIMA, GPH, FIGARCH and HYGARCH models. Long memory tests are performed both for the returns and volatilities. The results suggest that long memory dynamics in the returns and volatility might be modeled by using the ARFIMA–FIGARCH model. Kasman and Torun (2007) examine the dual long memory property of the Turkish stock market by using daily returns. The results indicate that dual long memory dynamics in the returns and volatility might be modeled by using the ARFIMA-FIGARCH model. They also found that the evidence of long memory in volatility, however, shows that uncertainty or risk is an important determinant of the behavior of daily stock data in the Turkish stock market. Kang and Yoon (2007) investigate the dual long memory property by applying the ARFIMA–FIGARCH model to two daily Korean stock price indices. Their empirical results indicate that long memory dynamics in the returns and volatility can be adequately estimated by the joint ARFIMA–FIGARCH model. They also found that the assumption of a skewed Student-t distribution is better for incorporating the tendency of asymmetric leptokurtosis. Tang and Shieh (2006) investigate the long memory properties for daily closing prices of three stock index futures markets (S&P500, Nasdaq100 and Dow Jones) by estimating FIGARCH and HYGARCH models with different distributions. After calculating the Value-at-Risk (VaR) numbers by the estimated models, they found that the HYGARCH models with skewed Student-t distribution perform better based on the Kupiec LR tests. Vougas (2004) examines the long memory of returns in the Athens Stock Exchange along with volatility. By using ARFIMA-GARCH model, he found weaker evidence in favor of long memory.

Karanasos and Kartsaklas (2009) examine the dynamics of the range-based volatility and turnover volume and their respective uncertainties by using a bivariate dual long-memory model in the Korean market for the period 1995–2005. They found that, when taking into account structural breaks the order of integration of the conditional variance series decreases considerably. Kasman (2009) analyses sudden changes of volatility in the stock markets of the BRIC countries (Brazil, Russia, India and China) using the ICSS algorithm for the period 1990 to 2007 and examines their impacts on the persistence of volatility. His findings indicate that when endogenously determined sudden shifts in variance are taken into account in the GARCH model, the estimated persistence in return volatility is reduced significantly in every return series. Kang et al. (2009) investigate sudden changes in volatility and re-examined the persistence of volatility in Japanese and Korean stock markets during 1986-2008. By using the FIGARCH model and ICSS algorithm, they have determined that the identification of sudden changes is generally associated with global financial and political events. They have also demonstrated that controlling sudden changes effectively reduces the persistence of volatility or long memory. Korkmaz et al. (2009) examine long memory in Istanbul Stock Exchange (ISE) by using the ICSS algorithm in variance and ARFIMA-FIGARCH model. Their findings indicate that long memory does not exist in the equity return; however, it exist in volatility. Therefore, ISE is found as a weak form inefficient market due to volatility as it has a predictable component. Cheong et al. (2008) study the influences of structural break to the fractionally integrated time-varying volatility model in Malaysian stock markets from year 1996 to 2006. Their empirical results evidence substantially reduction in long memory clustering volatility after the inclusion of structural breaks in the volatility during the Asian crisis. Choi and Zivot (2007) analyze the evidence for long memory and structural changes in the five G7 countries' forward discount. They establish evidence for long memory by estimating the long memory parameter with and without structural breaks. After removing the breaks, they still find evidence of stationary long memory in each country's forward discount. Malik and Hassan (2004) study volatility persistence by detecting time periods of sudden changes in volatility by using the ICSS algorithm. By examining five major sectors from January 1992 to August 2003, they find that accounting for volatility shifts in the standard GARCH model considerably reduces the estimated volatility persistence.

3. METHODOLOGY

In this section, first the basic definitions and theoretic properties of the models are discussed. Then to investigate long memory in asset returns and volatility, the joint ARFIMA-FIGARCH models with normal, Student-t and skewed Student-t innovations presented. After detecting structural breaks in variance by using the ICSS algorithm, dummy variables are introduced to the joint ARFIMA-FIGARCH models to account for the structural breaks.

3.1. ARFIMA-FIGARCH Model

The Fractionally Autoregressive Integrated Moving Average (ARFIMA hereafter) model, which is generally used parametric approach for testing the long memory property in the financial return series, developed by Granger and Joyeux (1980) and Hosking (1981). The idea of this model is to consider the fractionally integrated process *I(d)* in the conditional mean. The model is characterized by the autocorrelation function which decays at a hyperbolic rate (Kang and Yoon, 2007). The ARFIMA(n, ξ, s) can be expressed as follows:

$$\psi(L)(1-L)^{\xi}(y_t-\mu)=\theta(L)\varepsilon_t \quad (1)$$

$$\varepsilon_t = z_t\sigma_t, \quad z_t \sim N(0,1) \quad (2)$$

where independently and identically distributed (i.i.d.) with a variance σ^2 , L denotes the lag operator, ξ is the fractional difference parameter, $\psi(L)=1-\psi_1 L-\psi_2 L-\cdots-\psi_n L^n$ and $\theta(L)=1-\theta_1 L-\theta_2 L-\cdots-\theta_s L^s$ are the autoregressive (AR) and moving-average (MA) polynomials with standing in outside of unit roots, respectively.

Following Hosking (1981), when -0.5< ξ <0.5, the y_t process is stationary and invertible. For such processes, the effect of shocks to ε_t on y_t decays at the slow rate to zero. If ξ =0, the process is stationary, so-called short memory, and the effect of shocks to ε_t on y_t decays geometrically. For ξ =1, the process follows a unit root process. If 0< ξ <0.5, then the process exhibits positive dependence between distant observations implying long memory. If -0.5< ξ <0, then the process exhibits negative dependence between distant observations, so-called anti-persistence or intermediate memory (Kang and Yoon, 2007:592).

Fractionally integrated processes which are a subclass of long memory processes have been investigated recently in volatility studies. For example Ding et al. (1993) showed that the autocorrelation coefficients of the squared daily stock returns decay very slowly. Similar research on the volatility has led to an extension of the ARFIMA representation in ε_t^2, leading to the FIGARCH model. To detect the long memory pattern in volatility, Baillie et al. (1996) proposed the Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH hereafter) model by extending the IGARCH model to allow for persistence in the conditional variance. The model also fills the gap between short and complete persistence. In contrast to an $I(0)$ time series in which shocks die out at an exponential rate, or an $I(1)$ series in which there is no mean reversion, shocks to an $I(d)$ time series with 0<d<1 decay at a slow hyperbolic rate (Tang and Shieh, 2006:439). The FIGARCH (p, d, q) can be expressed as follows:

$$\phi(L)(1-L)^d \varepsilon_t^2 = w + [1-\beta(L)]v_t \quad (3)$$

where $\phi(L) \equiv \phi_1 L - \phi_2 L^2 - \cdots - \phi_q L^q$, $\beta(L) \equiv \beta_1 L - \beta_2 L^2 - \cdots - \beta_p L^p$ and $v_t \equiv \varepsilon_t^2 - \sigma_t^2$. The process can be interpreted as the innovations for the conditional variance and has zero mean serially uncorrelated.

The FIGARCH model offers greater flexibility for modeling the conditional variance, as it accommodates the covariance stationary GARCH model for d=0 and the non-stationary IGARCH model for d=1. Thus, the attraction of the FIGARCH model is that, for 0<d<1, it is sufficiently flexible to allow for intermediate range of persistence. Rearranging the terms in Eq.(3), an alternative representation for the FIGARCH (p, d, q) model can be rewritten as follows:

$$[1-\beta(L)]\sigma_t^2 = w + \left[1-\beta(L)-\phi(L)(1-L)^d\right]\varepsilon_t^2 \quad (4)$$

The conditional variance of ε_t^2 is obtained by:

$$\sigma_t^2 = \frac{w}{[1-\beta(L)]} + \left[1 - \frac{\phi(L)}{[1-\beta(L)]}(1-L)^d\right]\varepsilon_t^2 \quad (5)$$

That is:

$$\sigma_t^2 = \frac{w}{[1-\beta(L)]} + \lambda(L)\varepsilon_t^2 \quad (6)$$

where $\lambda(L) = \lambda_1(L) + \lambda_2(L)^2 \ldots$ Baillie et al. (1996) state that the impact of a shock on the conditional variance of the FIGARCH (p,d,q) processes decrease at a hyperbolic rate when 0<d<1. Hence, the long-term dynamics of the volatility is taken into account by the fractional integration parameter d, and the short-term dynamics is modeled through the traditional GARCH parameters.

3.2. Testing for Multiple Structural Breaks in Unconditional Variance

Inclan and Tiao (1994) proposed a method that based on Iterated Cumulative Sums of Squares (ICSS) algorithm to detect multiple structural breaks in the unconditional variance of a time series. The ICSS algorithm is utilized to identify discrete subperiods of changing volatility of stock returns. It assumes that the variance of a time series is stationary over an initial period of time, until a sudden change occurs as the result of a sequence of financial events; the variance then reverts to stationary until another market shock occurs. This process is repeated over time, generating a time series of observations with an unknown number of changes in the variance (Kang et al., 2009: 3544).

Let ε_t denote an independent time series with mean 0 and unconditional variance . The variance in each interval is given by $\sigma_j^2, j = 0,1,...,N_T$, where N_T is the total number of variance changes (breakpoints) in T observations and $1 < K_1 < K_2 < \cdots < K_{N_T} < T$ are the set of change points. Then, the variance over the N_T intervals is defined as follows (Malik and Hassan, 2004:213):

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < K_1 \\ \sigma_1^2, & K_1 < t < K_2 \\ \vdots & \\ \sigma_{N_T}^2, & K_{N_T} < t < T. \end{cases} \quad (7)$$

A cumulative sum of squares is utilized to determine the number of changes in variance and the time point of each variance shift. The cumulative sum of squares from the first observation to the kth point in time is expressed as follows:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2, \qquad k = 1,\ldots,T \quad (8)$$

Define the statistic as follows:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \quad k = 1,\ldots,T \text{ and } D_0 = D_T = 0 \quad (9)$$

Note that if there are no changes in variance, the D_k statistic will fluctuate around zero and D_k will look like a horizontal line when plotted against k. However, if there are one or more changes in variance, then the statistic values drift up or down from zero. Significant changes in variance are determined by the critical values obtained from the distribution of D_k under the null hypothesis of homogeneous (constant) variance. If the maximum absolute value of D_k is greater than the critical value, then the null hypothesis of homogeneous variance is rejected. If we assume k* to be the value at which $\max_k |D_k|$ is reached, then k* is taken as the time point of a variance change if $\max_k \sqrt{(T/2)}|D_k|$ falls outside the predetermined boundaries. The term $\sqrt{(T/2)}$ is required for the standardization of the distribution. In accordance with the study of Aggarwal et al. (1999), the critical value of 1.358 is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{(T/2)}|D_k|$. Therefore, upper and lower boundaries can be established at ±1.358 in the D_k plot. A change point in variance is identified if it exceeds these boundaries. To overcome this problem of detecting multiple change points in a series due to the "masking effects," Inclan and Tiao (1994) developed this algorithm that evaluates different pieces of a series for identification of change points in variance. The ICSS algorithm works by evaluating D_k over sample periods determined by the breakpoints from the D_k plot (Malik and Hassan, 2004:213; Inclan and Tiao, 1994:913-916).

Recent empirical studies have argued that the GARCH type models tend to overestimate volatility persistence when structural breaks or regime shifts in conditional variance are prevalent and ignored. In an effort to get reliable estimates of the model parameters, structural breaks should be incorporated via dummy variables ($D_1,\dots,D_n$) into the standard GARCH type models. The dummy variables take a value of one from each point of structural break of variance onwards, and take a value of zero elsewhere. Hereby, the sample FIGARCH (1, d, 1) model framework with multiple structural breaks that were identified via the ICSS algorithm can be obtained as follows:

$$h_t = w(1-\beta)^{-1} + \left[\left(1-(1-\beta(L)\right)^{-1}\left(1-\alpha(L)\right)^{-1}\left(1-(L)\right)^{d}\right]\varepsilon_t^2 + \left[d_1 D_1 + \cdots + d_n D_n\right] \quad (10)$$

4. DATA AND EMPIRICAL RESULTS

This section shows the descriptive analysis of data and provides the empirical findings of the models. The daily returns of five stock market price indices are analyzed with dual long memory models to capture the long-term dependence in these time series. Computations were performed with WinRats 6.0, Eviews 5.0 and G@RCH 4.2 which is Ox package designed for the estimation of various time series models. The characteristics of the data are presented in the first subsection. The next subsections show the estimated results of long memory models specifications and the corresponding qualification tests. To conserve space the results of the models with other distributions declined to present although they are available upon request.

4.1. Preliminary Analysis of the Data

The paper considers the national stock market closing prices for five countries. These countries and their respective price indices are: USA (S&P500), UK (FTSE100), Germany (DAX), France (CAC40) and Turkey (ISE100). The data obtained from the Yahoo Finance: World Indices database and the Istanbul Stock Exchange for the period January 2, 1991 to May 18, 2009. For each national stock market price indices, the continuously compounded rate of return was calculated as $r_t = \ln(p_t / p_{t-1})$ where p_t is the closing price on day t.

The descriptive statistics are summarized in Table 1. It is not surprising that series exhibit asymmetric and leptokurtic (fat tails) properties. Both skewness and excess kurtosis statistics indicate that the return series tend to have a higher peak and fatter-tail distribution than a normal distribution. Also the Jarque-Bera statistic is highly significant for each of the models indicating non-normality of the data. In addition, all the stock market return series are negatively skewed. In order to test the hypothesis of independence, Ljung–Box statistics are estimated for the return residuals [Q(20)] and squared return residuals [Q^2(20)]. The return residuals and the squared return residuals fail to be an independently and i.i.d. process, since the return and squared return residuals are highly correlated up to 20th lag. In particular, Q^2(20) statistics are extremely high, indicating the pervasive influence of volatility clustering in all markets.

Table 1: Descriptive Statistics of the Data

	S&P500	FTSE100	DAX	CAC40	ISE100
No. of observation	4631	4641	4639	4641	4577
Mean	0.0002213	0.000159	0.000273	0.000166	0.001527
Minimum	-0.094695	-0.092646	-0.098709	-0.094715	-0.199790
Maximum	0.109570	0.093842	0.107970	0.105950	0.177740
Standard deviation	0.011826	0.011594	0.014730	0.014208	0.028789
Skewness	-0.262120	-0.096343	-0.086439	-0.032641	-0.010206
Excess Kurtosis	10.6820	6.7887	5.1382	4.9790	3.4964
Jarque-Bera	21531.0	8915.3	5108.8	4794.6	2301.4
Q(20)	102.136	113.543	46.5708	73.6169	54.2467
Q^2(20)	6020.88	5621.33	3932.57	4052.48	1424.46

Note: The Q(20) and Q^2(20) are the Ljung-Box statistics for the return residuals and the squared return residuals for up to 20th-order serial correlation, respectively.

From the return graphs presented in Figure 1, several volatility periods can visually be observed. These graphical expositions show that all of the return series exhibit volatility clustering which means that there are periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes.

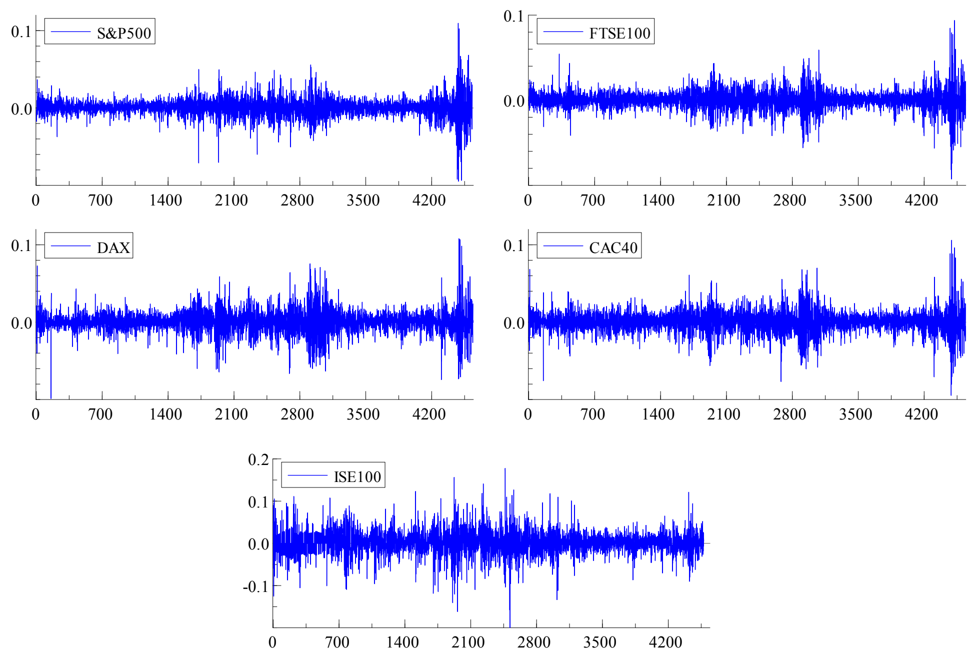

Figure 1: Daily Log-Returns For National Stock Market Price Indices
Note: S&P500 (USA), FTSE100 (UK), DAX (Germany), CAC40 (France), ISE100 (Turkey).

Before testing for the long memory property in returns and volatility, all return series are subjected to three unit root tests to determine whether stationarity $I(0)$. The null hypothesis of the ADF (Augmented-Dickey–Fuller) and PP (Phillips–Peron) tests is that the series has unit root, $I(1)$ process, while the KPSS (Kwiatkowski, Phillips, Schmidt, and Shin) test has the null hypothesis of stationarity, $I(0)$ process.

The empirical results of stationarity tests for all sample returns are presented in Table 2. Large negative values for the ADF and PP tests for all returns support the rejection of the null hypothesis of a unit root at the 1% significance level. Additionally, the statistics of the KPSS test indicate that all return series are insignificant to reject the null hypothesis of stationarity, implying that they are stationary processes. Thus, all return series are stationary $I(0)$ and suitable for subsequent long memory tests in this study.

Table 2: The Unit Root Tests for Sample Returns

	S&P500	**FTSE100**	**DAX**	**CAC40**	**ISE100**
ADF test	-18.40 (20)[b]	-11.62 (35)[b]	-9.25 (45)[a]	-10.89 (35)[a]	-19.49 (9)[b]
PP test	-73.27 (21)[b]	-69.97 (6)[a]	-69.06 (13)[a]	-69.47 (21)[a]	-63.63 (13)[b]
KPSS test	0.079 (24)[d]	0.054 (9)[d]	0.245 (14)[c]	0.312 (22)[c]	0.045 (15)[d]

Notes: MacKinnon's critical values at the 1% significance level for ADF and PP tests are (a) -2.57 (without constant and trend) and (b) -3.96 (with constant and trend). KPSS critical values are (c) 0.739 (with constant) and (d) 0.216 (with constant and trend) at the 1% significance level. Maximum lag orders are in the parentheses.

4.2. Estimation Results of the Joint ARFIMA-FIGARCH Models

In this section, first the long memory property in conditional mean and conditional variance is considered separately. Following Cheung (1993), all the possible combinations for the ARMA (n,s) with n = 0, 1, 2 and s = 0, 1, 2 are considered. According to the estimation results and diagnostic statistics of

ARFIMA (n, ξ, s) models all stock market returns fit to an ARFIMA (2,ξ,2) model for a long memory process. Then, the FIGARCH specifications in modeling a long memory volatility process with different orders of (p,q) are considered. Based on the model selection criteria the FIGARCH (1,d,1) model performs as the best fitting specification for all cases. Therefore it seems quite while worthy to analyze the dual long memory property in both the conditional mean and conditional variance since long memory dynamics are commonly observed in both of them. As a result, it is worthwhile that the dual long memory tests should be simultaneously done in returns and volatility.

Table 3 reports the estimation results of the joint ARFIMA–FIGARCH models under skewed Student-t distribution (SkSt). To conserve space the results of the models with other distributions declined to present. The ARFIMA (2,ξ,2)-FIGARCH (1,d,1) specification is found to be the most successfully model

Table 3: Estimation results of the joint ARFIMA (2,ξ,2)-FIGARCH (1,d,1) models

	S&P500	FTSE100	DAX	CAC40	ISE100
μ	0.0005 (0.0001)	0.0005 (0.0002)	0.0007 (0.0002)	0.0005[a] (0.0002)	0.0019 (0.0004)
ψ_1	-0.1608[a] (0.0709)	1.4105 (0.0706)	0.0076* (0.1233)	-0.2034 (0.0558)	-0.9545 (0.2819)
ψ_2	-0.6221 (0.0542)	-0.4453 (0.0604)	0.5722 (0.1018)	0.6683 (0.0504)	-0.6960 (0.2189)
ξ	**0.0696[b]** **(0.0392)**	**0.2213[b]** **(0.1212)**	**0.0839[b]** **(0.0462)**	**0.1231** **(0.0470)**	**0.0353[a]** **(0.0149)**
θ_1	0.0478* (0.0624)	-1.6462 (0.1163)	-0.1114* (0.1239)	0.0606* (0.0447)	0.9748 (0.2738)
θ_2	-0.7095 (0.0513)	0.6542 (0.1104)	-0.6063 (0.1026)	-0.7654 (0.0364)	0.7134 (0.2262)
ω	0.0001 (0.0000)	0.0001 (0.0000)	0.0002[a] (0.0000)	0.0003 (0.0001)	0.0015 (0.0006)
α	0.1635 (0.0344)	0.1509 (0.0379)	0.0947 (0.0310)	0.1549 (0.0331)	0.1122* (0.1145)
β	0.6414 (0.0567)	0.6090 (0.0552)	0.6199 (0.0494)	0.6660 (0.0543)	0.4082 (0.1375)
d	**0.4947** **(0.0500)**	**0.5146** **(0.0416)**	**0.5494** **(0.0451)**	**0.5450** **(0.0527)**	**0.4289** **(0.0464)**
υ	7.2562 (0.7140)	13.2883 (2.4557)	9.2240 (1.3168)	11.2719 (1.8841)	7.5503 (0.7907)
ln(ζ)	-0.0758 (0.0190)	-0.0951 (0.0241)	-0.0981 (0.0204)	-0.0938 (0.0222)	0.0074* (0.0201)
ln(*L*)	15221	15110	13981	13927	10367
AIC	-6.5682	-6.5061	-6.0224	-5.9967	-4.5248
BIC	-6.5515	-6.4895	-6.0057	-5.9800	-4.5079
Skewness	-0.4956	-0.2118	-0.7490	-0.3820	-0.1515
Excess Kurtosis	2.3215	0.8874	7.0486	1.8344	1.6539
J-B	1230	187	10037	764	539
***Q*(20)**	34.0517	26.6196	24.1326[b]	15.7131	26.3890[a]
Q^2(20)	13.0304	25.5267	4.8020	14.2225	27.0592[b]
ARCH(5)	1.3884	0.3628	0.0646	1.4526	1.1352
***P*(60)**	78.2162	54.5010	97.4044	55.5352	152.9585

Notes: Standard errors are reported in parentheses below corresponding parameter estimates. 1n(*L*) is the value of the maximized Gaussian log-likelihood, AIC is the Akaike information criteria and BIC is the Bayesian information criteria. The *Q*(20) and Q^2(20) are the Ljung–Box test statistics with 20 degrees of freedom based on the standardized residuals and squared standardized residuals respectively. The ARCH(5) denotes the ARCH test statistic with lag 5. *P*(60) is the Pearson goodness-of-fit statistic for 60 cells.
a and b indicate significance levels at the 5% and 10% respectively. * indicates insignificancy.

for capturing the dual long memory property for all stock market returns. In the estimates of the joint ARFIMA–FIGARCH models, both long memory parameters, ξ and d are significantly different from zero and have positive sign, implying that the dual long memory property is prevalent in the returns and volatility of all stock markets.

The SkS*t* distribution is found to outperform the normal distribution since the t-statistics of the tail parameter (υ) highly significant in all stock market returns. In addition, the asymmetric parameters $ln(\zeta)$ are unequal to zero and significant negative so that the density is skewed to the left side, except ISE100. In addition, the lowest values of *P*(60) test statistics verify again the relevance of SkSt distribution for all stock market returns. Thus, the SkSt distribution can be used to capture the tendency of stock return distribution referring to leptokurtosis.

The long memory in the conditional mean implies that stock prices follow a predictable behavior that is unsuitable with the weak form EMH. As discussed before, in finance, the weak form EMH asserts that information is quickly and efficiently incorporated into asset prices at any point in time, so that past price information cannot be used to predict future price movements. The evidence of long memory in volatility, however, shows that uncertainty or risk is an important determinant of the behavior of daily stock data in all stock markets.

In an effort to get reliable estimates of the model parameters, the structural breaks in volatility are detected by the ICSS algorithm and given in Table 4. At the 95th percentile level, the number of breakpoints in variance of return series for S&P500, FTSE100, DAX, CAC40 and ISE100 are 16, 30, 32, 29 and 40 respectively. Because of too many breakpoints are detected, the critical value of 1.628 at the 99th percentile level is used and breakpoints declined. Due to shortcomings as unknowing the maximum number of breakpoints and the minimum distance restriction between breakpoints, Potter and Dijk (2004) imposed a second restriction in the ICSS algorithm. They imposed minimum distance restriction between breakpoints for daily data as 63 or 126 business days (three or six months, respectively). In this paper, 63 business days is selected. After taking into account this proposition, some of the breakpoints are eliminated. The remaining breakpoint dates are given and the same or nearby breakpoint dates for different stock markets are shaded in Table 4.

Table 4: Structural Breaks in Volatility

S&P500	FTSE100	DAX	CAC40	ISE100	S&P500	FTSE100	DAX	CAC40	ISE100
		17.03.'91							17.11.'00
		16.08.'91					23.08.'01		03.03.'01
20.04.'92	08.04.'92	16.07.'92		02.03.'92					06.12.'01
	21.10.'92				14.06.'02	11.06.'02	13.06.'02	03.06.'02	01.11.'02
	26.11.'93		05.02.'93	29.01.'93	02.04.'03	08.04.'03	07.04.'03	11.03.'03	
				07.01.'94	01.10.'03		09.10.'03		26.09.'03
	20.12.'94	24.11.'94		17.06.'94	11.05.'04	20.05.'04	19.05.'04	28.10.'04	
15.12.'95						28.04.'06		11.05.'06	
			03.01.'96			26.02.'07	26.02.'07		
		04.12.'96	02.12.'96		09.07.'07			17.07.'07	06.07.'07
26.03.'97	29.05.'97	21.07.'97					14.01.'08		
22.10.'97				24.10.'97	12.09.'08	12.09.'08	26.09.'08	18.09.'08	10.09.'08
		02.01.'98							
		04.08.'98		07.08.'98					
		13.01.'99		25.11.'99					

The important global and political fluctuations for the period 1991-2009 can be broken-down as follows: 1991-1992 (The Gulf Crisis), 1994 (Financial Crisis in Turkey), 1997 and 1998 (Asian Crisis), 1999 (The Marmara Earthquake in Turkey and Russian Crisis), 2000 and 2001 (Financial Crises in Turkey and Argentina, and Terror attacks hit USA.), 2003 (Iraq War), 2006 (European Gas Crisis, Oil Crisis, Subprime Mortgage Crisis), 2007 (Liquidity Crisis) and 2008 (Global Crisis). As can be seen in Table 4, intensity of the structural breaks happened mostly at 2008.

The next step is to join these structural breaks in variance via dummy variables in the joint ARFIMA-FIGARCH models. For comparing the model parameters with and without dummy variables, the estimated results are given alongside columns. Table 5 shows that after the inclusions of dummy variables in the joint ARFIMA-FIGARCH models, the volatility persistence $(\alpha+\beta)$ is significantly reduced in all stock market returns except ISE100. It appears that the presence of long memory in volatility is spuriously generated by ignoring structural breaks in conditional variances. Also, the long persistence clustering volatility (fractional differencing parameter) indicates substantial reductions in all stock market returns. In addition, the estimated residuals from models with dummy variables show the smaller values of skewness, kurtosis and J-B tests in contrast to the residuals from models without dummy variables. Thus, distinctive improvements reached in model selection evaluations.

Table 5: ARFIMA-FIGARCH Parameters With and Without Dummy Variables

	Without Dummy Variables					**With Dummy Variables**				
	S&P500	**FTSE100**	**DAX**	**CAC40**	**ISE100**	**S&P500**	**FTSE100**	**DAX**	**CAC40**	**ISE100**
ξ	**0.070**[b]	**0.221**	**0.084**[b]	**0.123**	**0.035**[a]	**0.063**	**0.025**	**0.077**	**0.105**	**0.027**
α	0.164	0.151	0.095	0.155	0.112*	0.163	0.064	0.181	0.148	-0.582*
β	0.641	0.609	0.620	0.666	0.408	0.341	0.099	0.331	0.213	-0.559*
$\alpha+\beta$	**0.805**	**0.7609**	**0.715**	**0.821**	**0.520**	**0.504**	**0.163**	**0.513**	**0.361**	**-1.141***
d	**0.495**	**0.515**	**0.549**	**0.545**	**0.429**	**0.181**	**0.044**	**0.134**	**0.070**	**0.068**
ln(*L*)	15221	15110	13981	13927	10367	15266	15213	14099	14015	10483
AIC	-6.568	-6.506	-6.022	-5.997	-4.525	-6.581	-6.538	-6.060	-6.022	-4.558
BIC	-6.552	-6.490	-6.006	-5.980	-4.508	-6.542	-6.480	-5.998	-5.967	-4.485
Skewness	-0.496	-0.2118	-0.749	-0.382	-0.1515	-0.314	-0.062	-0.097	-0.139	0.017
Excess Kurtosis	2.322	0.887	7.049	1.834	1.654	1.664	0.440	0.455	1.059	0.586
J-B	1230	187	10037	764	539	610	40	47	232	66
$Q(20)$	34.052	26.620	24.133[b]	15.713	26.389[a]	33.375[a]	22.039	17.595	10.684	19.757
$Q^2(20)$	13.030	25.527	4.802	14.223	27.059[b]	12.692	24.563	13.411	16.555	33.214[a]
ARCH(5)	1.388	0.363	0.065	1.453	1.135	0.950	1.319	0.369	0.922	1.095
$P(60)$	78.216	54.501	97.404	55.535	152.959	70.313	58.121	66.570	56. 518	207.728

a and b indicate significance levels at the 5% and 10% respectively. * indicates insignificancy.

5. CONCLUSIONS

The purpose of this study is to examine the dual long memory properties for five stock market returns by using joint ARFIMA-FIGARCH model and structural break test in context of the weak form efficient market hypothesis. The joint ARFIMA-FIGARCH models are estimated by using daily closing prices for S&P500 (USA), FTSE100 (UK), DAX (Germany), CAC40 (France) and ISE100 (Turkey). In an effort to assess the impact of structural breaks in volatility persistence, the breaks in variance are detected by using Iterated Cumulative Sums of Squares (ICSS) algorithm and dummy variables are incorporated into the models.

The empirical results show that, the joint ARFIMA $(2,\xi,2)$-FIGARCH $(1,d,1)$ specification with skewed Student-t distribution is found to be the best performing model. Also both long memory parameters ξ and d are significantly different from zero and have positive sign, implying that the dual long memory property is prevalent in the returns and volatility of all stock markets. The long memory in the conditional mean implies that stock prices follow a predictable behavior and the possibility of consistent speculative profits may arise, that is unsuitable with the weak form EMH. The evidence of long memory in volatility, however, shows that uncertainty or risk is an important determinant of the behavior of daily stock data in all stock markets.

After the inclusions of dummy variables in the ARFIMA-FIGARCH models, the volatility persistence $(\alpha+\beta)$ is significantly reduced in all stock market returns except ISE100. It appears that the presence of long memory in volatility is spuriously generated by ignoring structural breaks in conditional variances. Also, the long persistence clustering volatility (fractional differencing parameter) indicates substantial reductions in all stock market returns. In addition, distinctive improvements reached in model selection evaluations. It can be said that taking into consideration the structural breaks in the models help to traders having both long and specially short positions.

Finally, according to these results, volatility has a predictable structure and it indicates that all stock markets are weak form inefficient. Further, it is determined that incorporating information on structural breaks in variance improves the accuracy of estimating volatility dynamics and effectively reduces the persistence of volatility.

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