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AN EMPIRICAL INVESTIGATION OF ASYMMETRIC LONG MEMORY AND STRUCTURAL BREAKS IN THE VOLATILITY OF TURKISH STOCK MARKET

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Abstract

In this study, long memory and asymmetric properties in volatility of Turkey Stock Market are examined by using the FIGARCH, FIEGARCH and FIAPARCH models under different distribution assumptions as Normal and Skewed Student-t for the period 1990-2015. Furthermore, structural changes in volatility of Turkey Stock Market are investigated. The findings of the study display long memory property and the presence of asymmetric effects of shocks in volatility of Turkey Stock Market.

Index Terms— **Asymmetric Effect, Structural Break, FIAPARCH Model, FIEGARCH Model, FIGARCH Model**

INTRODUCTION

Hyperbolic decrease tendency of return and volatility in autocorrelation functions which means the property as rotating to slow average is defined as long memory. In case the existance of long term dependency among price movements, there is positive autocorrelation among price movements. In case of having Long Memory property, stock market prices will have a predictable structure and retrospective tendency of prices can be used for price estimations in future[1].

Long Memory dynamics are important indicators showing the existence of nonlinear relations in a time series' mean and variance. Along with the suggestions of [2] and [3] about

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ARCH and GARCH type models, modelling of stock exchange return volatility became a significant research area. It was found in these studies that stock market volatility changed in time and presented a positive serial correlation referred as volatility clustering. This situation shows that changes in volatility are not accidential however these models cannot assess the long memory property in volatility. Very slow mean-reverting process with hyperbolic rate of autocorrelation functions related to return and volatilities is defined as long memory in return and volatility. It is very important especially while taking financial investment decision and about whether financial market behaviours are linear in terms of monetary policies. Nonlinear structure of price movements in financial markets will cause that standard statistical analysis lead mistaken result while taking decision for investment. Therefore, complex structure of financial markets causes academicians, policy makers and investors approach to the markets with a different point of view.

Many studies in the literature focus on analyzing dual long memory property in conditional mean and volatility. In recent years, modelling long memory property becames attractive research area especially in stock market return and volatility. [4] investigates stock market prices of Turkey for the period of 1988-1994. The author finds that stock market prices have not random walk process and Turkey' stock market is not efficent market. [5] examine whether Spain Stock Market has long memory property by using daily data for the period 1980-1993. They couldn't obtain findings about long memory property in stock market. [6] investigate Greece Stock Market by using weekly data for the period 1981-1990. They show that Greece Stock Market is inefficient market in weak-form. [7] research the existing of long memory property in Brazilian Stock Market by using ARFIMA model. They find that stock market hasn't long memory property. [8] estimates ARFIMA model by using monthly data for the period 1960-1999 for stock market 16 OECD countries. The author displays that Denmark, Finland and Ireland Stock Markets have long memory. [9] analyze S&P500 index by using daily data for the period 1828-1991, and indicate that S&P500 index has long memory property. [10] investigates long memory property of Turkish Stock Market and he shows that Turkish Stock Market is not an efficient market. [11] finds that Athens Stock Market is an efficient market by using ARFIMA model for the period 1990-2000. [12] examine property of long memory in return and volatility of Turkish Stock Market by using ARFIMA-FIGARCH model. They shows that Turkish Stock Market isn't an efficient market. [13] researchs stock markets of Egypt, Jordan, Morocco and Turkey by using daily data for the period 1997-2002. He finds that evidence of long memory in the returns of stock markets related to these countries. [14] investigate existing of long memory in the return and volatility of Istanbul Stock Market. They display that volatility series has long memory property. [15] examines the long-term dependency of stock return volatility for 23 developing markets for the period 2000 – 2007. The author indicates persistence in return volatility for many markets including Indonesia. [16] research long memory in S&P500, FTSE100, DAX, CAC40 ve ISE100 stock markets by using ARFIMA-FIGARCH models. They

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find that all of the stock markets have dual long memory properties. [17] investigate the existing of dual long memory in Turkish Stock Market for the period 2010-2013 by using ARFIMA-FIGARCH model, and test efficient market hypothesis for Turkish Stock Market. The authors find that Turkish Stock Market is not an efficient stock market. [1] examines that whether Istanbul Stock Exchange is weak form efficient market. The author indicates that Turkish Stock Market has long memory.

The study includes testing of structural breaks and the analysis of long memory properties in volatility of Turkey stock exchange through FIGARCH, FIEGARCH and FIAPARCH models under different distribution assumptions as Normal and Skewed Student-t distributions for the period of (1990-2015).

I. METHODOLOGY

[18] and [19] suggested ARFIMA model in order to test long memory properties in returns. The purpose of this model is to assess fractional integrated process I(d) in conditional mean. The ARFIMA (p, ξ, d) model is expressed as (1).

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

Where, $\varepsilon_t = z_t\sigma_t,\quad z_t \sim N(0,1)$ and $(1-L)^{\xi}=\sum_{k=0}^{\infty}\frac{\Gamma(k-\xi)L^k}{\Gamma(-\xi)\Gamma(k+1)}$.

FIGARCH model has been suggested by [20] for the extended version of squared errors in ARFIMA model. FIGARCH (p,d,q) model is expressed as (2).

$$\phi(L)(1-L)^d\varepsilon_t^2=\omega+[1-\beta(L)]v_t \tag{2}$$

$v_t=\varepsilon_t^2-\sigma_t^2$ are serially uncorrelated errors having zero mean. ε_t^2 are squared errors of GARCH process. The process of $\{v_t\}$ is integrated for conditional variance σ_t^2 as variations. It is assumed that all roots of $\phi(L)$ *and* $[1-\beta(L)]$ stayed out of unit circle.

If d=0, then the process of FIGARCH (p,d,q) is reduced to the process of GARCH (p,q). If d=1, then the process of FIGARCH becomes an integrated process of GARCH (IGARCH). Shocks have an infinite effect on prospective volatility in this process.

As it is also indicated above, the model of FIGARCH (p,d,q) imposes an ARFIMA structure on ε_t^2. The Model (2) can be rearranged as follows.

$$[1-\beta(L)]\sigma_t^2=w+[1-\beta(L)-\phi(L)(1-L)^d]\varepsilon_t^2, \tag{3}$$

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Conditional variance of ε_t^2 is given with;

$$\sigma_t^2 = \frac{\omega}{[1-\beta(L)]} + \lambda(L)\varepsilon_t^2, \qquad (4)$$

where, $$\lambda(L) = 1 - \frac{\phi(L)}{[1-\beta(L)]}(1-L)^d \qquad (5)$$

[20] indicate in their studies that when 0≤d<1, the effect of a shock on conditional variances of FIGARCH (p,d,q) processes decreases with hyperbolic rates. In this respect, while short term dynamics of volatility are modelled with traditional GARCH model parameters, long term dynamics of volatility can be assessed with fractional integration parameter as d.

Asymmetric effects of shocks can not be evaluated by FIGARCH model. For this purpose, [21] propose FIEGARCH model. FIEGARCH (p, d, q) model can be expressed as follows;

$$\phi(L)(1-L)^d \ln h_t = \beta_0 + \sum_{i=1}^{q}(\beta_i|x_{t-i}| + \gamma_i x_{t-i} \qquad (6)$$

$$\ln(h_t) = w + \phi(L)^{-1}(1-L)^{-d}[1+\alpha(L)]g(z_{t-1}) \qquad (7)$$

$$g(z_t) = \theta(z_t) + \gamma[|z_t| - E|z_t|] \qquad (8)$$

In (8), first term $\theta(z_t)$ shows sign effect, second term $\gamma[|z_t| - E|z_t|]$ shows magnitude effect. For FIEGARCH (p, d, q) model; if d=0, then the process of FIEGARCH becomes an EGARCH model. if d=1, then the process of FIEGARCH becomes an IEGARCH model [21]. Furthermore, FIAPARCH model which evaluates asymmetric effect of shocks on volatility is proposed by Tse(1998). FIAPARCH model is as follows;

$$\sigma_t^\delta = w + \{1-[1-\beta(L)]^{-1}\phi(L)^{-1}(1-L)^d\}(|\varepsilon_t| - \gamma\varepsilon_t)^\delta + \beta(L)\sigma_t^\delta \qquad (9)$$

Where, d is long memory parameter. According to [22], asymmetry parameter is 1<γ<1. If γ>0, then negative shocks (bad-news) cause more volatility than positive shocks (good-news).

II. EMPIRICAL RESULTS

Data used in the study consists of daily stock index data for the period of 01.02. 1990 - 24.03.2015 including the periods of economic crisis. Daily logarithmic returns in t-time related to the stock markets of Turkey (Stock Exchange İstanbul-BIST100) are;

$$R_t = \ln(P_t / P_{t-1})x100, \; \text{t=1,2,….n.} \qquad (10)$$

Where R_t indicates index return in t-time, P_t is the closure price of index in t-time, P_{t-1} is the closure price of index in (t-1) time. BIST100 data was obtained from the web site of

Stock Exchange Istanbul. Descriptive statistics related to stock index returns of Turkey (RBIST) is given in Table 1.

TABLE I:Descriptive Statistics of Return Series

	RBIST
Mean:	**0.124858**
Standard Deviation:	**2.582696**
Skewness:	**-0.056252**
Kurtosis:	**7.572717**
Minimum:	**-19.97851**
Maximum:	**17.774**
J-B:Prob.	**5736.225 (0.0000)**
ARCH (2):	**365.21****
ARCH (5):	**179.46****
ARCH (10):	**92.643****
Q(5):	**45.0690****
Q(10):	**65.9260****
Q(20):	**78.1050****
Q(50):	**115.945****

TABLE I:Descriptive Statistics of Return Series (Continuing)

Q^2(5):	**1389.36****
Q^2(10):	**1797.41****
Q^2(20):	**2419.29****
Q^2(50):	**3592.99****
**** shows statistical significantly at level %5**	

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According to the results in Table 1, we may assert that skewness parameter of RBIST return series is negative and the value of leptokurtosis is high. According to relevant statistics, it indicates that RBIST return series shows symmetric properties and more leptocurtic and fat tail compared to the normal. Moreover, the statistic of Jarque-Bera having a relatively high value is also statistically significant as an indication related to return series non-normal distribution. For independency test of return error and squared return error series, Ljung-Box statistics (Q and Q^2) in various delays are estimated. According to statistics, i.i.d. (property of independent and identically distributed) process is not observed since RBIST return errors and squared return errors highly correlated up to 50th delay. In high degrees especially showing extensive effect of volatility clusters in stock exchange returns, statistical value in 50th delay is also significant. Findings of ARCH-LM test also indicate the existence of significant ARCH effects in standardised errors. Q and Q^2 statistics present an evidence of "Long Memory" property in squared return series considered as the most popular Proxy for volatilities in financial markets.

Three different unit root test results as ADF (Augmented Dickey Fuller), PP (Phillips-Perron) and KPSS (Kwiatkowski, Phillips, Schmidt ve Shin) are given in Table 2 in order to determine whether the series is stationary I(0) before long memory test for stock exchange return series (RBIST) in the study.

TABLE II:Unit Root Tests for Return Series

Tests	RBIST
ADF	-75.14515**
PP	-75.49833**
KPSS	0.458625
** indicates the refusal of unit root null hypothesis in the significance level at %5. (McKinnon Critical Value is [-2.865], Kwiatkowski Critical Value is [0.463000])	

According to the results in Table 2, while high negative results of ADF and PP tests indicates the refusal of unit root null hypothesis for all return series at the significance level of 5%, KPSS test statistics do not refuse null hypothesis showing I(0) process for all return series at the significance level of 5%. The results of unit root tests are supported stationary for return series RBIST. Long memory property in volatility will be also analysed by using FIGARCH. The results of FIGARCH Model for long memory in volatility of RBIST are shown in Table 3.

TABLE III: The Results of FIGARCH(1,d,1) Model

p=1,q=1	FIG ARCH	
	N	SST
ω	0.200762** (0.060613) [0.0009]	0.227308** (0.062903) [0.0003]
β_0	0.209146** (0.073959) [0.0047]	0.188497** (0.077745) [0.0154]
β_1	0.459228** (0.082112) [0.0000]	0.432815 (0.086189) [0.0000]
d	0.369012** (0.036641) [0.0000]	0.365441** (0.032395) [0.0000]
v	-	6.286434** (0.44084) [0.0000]
ln(ζ)	-	-0.040131** (0.013850) [0.0038]
Log(L)	-14583.402	14410.576
AIC	4.433861	4.381938
SIC	4.437990	4.388131

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TABLE III: The Results of FIGARCH(1,d,1) Model (Continuing)

Çarpıklık	-0.05625	-0.24230
Aşırı Basıklık	7.57272	2.1546
J-B	1335.5	1337.2
Q(5)	56.6537**	56.6284**
Q(10)	70.0480**	70.0557**
Q(20)	82.6462**	82.6306**
Q(50)	113.743**	113.629**
$Q^2(5)$	1.18495	1.00583
$Q^2(10)$	5.77109	5.73504
$Q^2(20)$	10.4536	10.6981
$Q^2(50)$	43.2928	43.6789
ARCH(5)	0.27309 [0.9280]	0.23376 [0.9478]
ARCH(10)	0.59830 [0.8166]	0.59112 [0.8226]
P(40)	645.1064**	486.4924**
P(50)	787.1581**	629.8176**
P(60)	956.1277**	743.9757**
, * indicate statistically significant 5% and 10% Respectively. ( ) indicates standard error, [ ] indicates P-values. P(40), P(50) ve P(60) indicate , Pearson Goodness of Fit for 40, 50, 60 cells.		

From Table 3, long memory d parameter for FIGARCH model under normal and skewed student-t distributions is significantly different from zero for RBIST return series and the volatility demonstrates long memory process. Moreover, we can say that return series demonstrates i.i.d. property according to Ljung-Box test statistics. The results of Pearson Goodness of Fit Test indicate that different distributions are also appropriate for RBIST.

Similarly, the results of FIEGARCH and FIAPARCH model which evaluate asymmetric effects are presented Table 4 and Table 5.

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TABLE IV: The Results of FIEGARCH(1,d,1) Model

p=1,q=1	N	SST
ω	2.957430** (0.26990) [0.0000]	1.986055** (0.51793) [0.0001]
β_0	0.346170 (0.33263) [0.2980]	0.254079 (0.29660) [0.3917]
β_1	0.283293 (0.25381) [0.2644]	0.438322** (0.17011) [0.0100]
(Egarch)θ_1	- 0.035758** (0.011440) [0.0018]	- 0.049649** (0.011101) [0.0000]
(Egarch)θ_2	0.217621** (0.033585) [0.0000]	0.217865** (0.031950) [0.0000]
d	0.566058** (0.044013) [0.0000]	0.539609** (0.046075) [0.0000]
v	-	5.597771** (0.39864) [0.0000]
ln(ξ)	-	-0.005977 (0.014069) [0.6710]
Log(L)	-14617.617	-14420.424
AIC	4.444868	4.385539
SIC	4.451062	4.393797
Çarpıklık	-0.19894	-0.15557
Aşırı Basıklık	2.4429	2.4955
J-B	1679.5	1734.0

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TABLE IV: The Results of FIEGARCH(1,d,1) Model (Continuing)

Q(5)	56.3108**	63.5622**
Q(10)	71.2946**	78.7503**
Q(20)	84.6118**	92.9395**
Q(50)	114.359**	122.129**
$Q^2(5)$	9.20043**	10.5577**
$Q^2(10)$	19.8897**	19.7384**
$Q^2(20)$	28.5809	27.3234
$Q^2(50)$	63.4799	61.9314
ARCH(5)	1.8150 [0.1063]	2.1140 [0.0607]
ARCH(10)	1.9012[0.0403]*	1.9018[0.0402]*
P(40)	670.6991**	513.6900**
P(50)	816.3374**	614.0881**
P(60)	1026.1216**	776.6201**
, * indicate statistically significant 5% and 10% respectively. ( ) indicates standard error, [ ] indicates p-values. P(40), P(50) ve P(60) indicate , Pearson Goodness of Fit for 40, 50, 60 cells.		

From Table 4, long memory d parameter for FIEGARCH model under normal and skewed student-t distributions is significantly different from zero for RBIST return series and the volatility demonstrates long memory process. Furthermore, return error series has not i.i.d. property according to Ljung-Box Q and Q^2 test statistics except $Q^2(20)$ and $Q^2(50)$. The results of Pearson Goodness of Fit Test indicate that skewed student-t distribution also appropriate for RBIST.

Moreover, the asymmetry term θ_1 is statistically significant. Negative coefficient implies that negative shocks cause higher volatility in returns than positive shocks.

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TABLE V: The Results of FIAPARCH(1,d,1) Model

p=1,q=1	N	SST
ω	0.088994 (0.093369) [0.3406]	0.162340*** (0.097168) [0.0948]
β_0	0.117852 (0.093523) [0.2077]	0.058498 (0.12175) [0.6309]
β_1	0.284986** (0.11551) [0.0136]	0.227830*** (0.14221) [0.1092]
(Aparch)γ	0.113658** (0.033607) [0.0007]	0.147392** (0.031853) [0.0000]
(Aparch) δ	2.281885** (0.10460) [0.0000]	2.252681** (0.10004) [0.0000]
d	0.286499** (0.051268) [0.0000]	0.289341** (0.041834) [0.0000]
v		6.089823** (0.44328) [0.0000]
ln(ξ)		-0.033229** (0.014193) [0.0192]
Log(L)	-14564.744	-14395.123
AIC	4.428797	4.377849
SIC	4.434991	4.386107
Çarpıklık	-0.20846	-0.19437
Aşırı Basıklık	2.1275	2.1465

J-B	1288.6	1304.6
Q(5)	62.4541**	64.6893**
Q(10)	76.2706**	78.7895**
Q(20)	89.0179**	91.9261**

TABLE V: The Results of FIAPARCH(1,d,1) Model (Continuing)

Q(50)	119.599**	121.929**
$Q^2(5)$	0.552177	1.28056
$Q^2(10)$	4.59133	5.75471
$Q^2(20)$	9.11428	11.0014
$Q^2(50)$	43.6209	46.2251
ARCH(5)	0.11567[0.9890]	0.25560[0.9372]
ARCH(10)	0.45717[0.9178]	0.56116[0.8467]
P(40)	641.0942**	489.1185**
P(50)	784.7416**	604.4681**
P(60)	967.8906**	732.8693**
, * indicate statistically significant 5% and 10% respectively. ( ) indicates standard error, [ ] indicates p-values. P(40), P(50) ve P(60) indicate , Pearson Goodness of Fit for 40, 50, 60 cells.		

According to Table 5, long memory parameter in volatility d is statistically significant, and the power term δ is statistically significant at 5% level. Estimated asymmetry coefficient γ is significant and positive implying that negative shocks result in higher volatility than positive shocks. In other words, the positive sign of γ suggests that "bad news" decrease is more destabilizing than "good news", i.e. an unanticipated increase.

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To obtain reliable estimates of model parameters, structural breaks in volatility have been investigated by using algorithms of ICSS [23], ICSS(Kappa-1) and ICSS(Kappa-2) developed by [24]. The algorithm of ICSS Inclan Tiao (IT) shows 46 structural break. In addion, the algorithms of ICSS(Kappa-1) and ICSS(Kappa-2) display 21 and 6 structural breaks in variance respectively. the dates of breaks in conditional variance according to ICSS (K-1) and ICSS (K-2) are displayed in Table 6[2].

[2] [25] display that in case of serial correlation in residuals, ICSS test misrepresents the size of structural break in unconditional variances. Therefore, a new method is necessary to account for serial dependence of residuals. Furthermore, [25] and [24] indicate upward bias in estimation of ICSS statistic whenever returns follow GARCH process. Moreover, the assumption of ε_t~iid N(0, σ^2) is inappropriate since residuals have leptocurtic distribution. [26] report that these assumptions cause over estimation of the number of breaks using the ICSS test. Our results show a non-normal distributions of returns, serial correlation, heteroskedasticity and “fat-tailed” Leptokurtic distribution. Therefore, ICSS test alone may not be appropriate for this study. For this purpose, we use Inclan-Tiao, Kappa-1 (K-1) and Kappa-2 (K-2) tests of [24] Therefore, the results of estimation with dummy variable for structural breaks in variance through Kappa-1(K-1) and Kappa-2 (K-2).

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TABLE VI: Structural Breaks in Volatility of RBIST

ICSS(*K-1*)	ICSS(*K-2*)
1992-07-09	1992-02-21
1993-01-28	1997-10-23
1994-01-06	2001-12-05
1994-03-01	2004-03-03
1994-05-09	2008-01-17
1997-10-23	2009-05-19
1998-02-20	
1998-08-06	
1998-11-24	
2000-11-16	
2001-07-18	
2002-10-31	
2003-03-24	
2003-09-25	
2004-02-18	
2008-01-17	
2009-05-19	
2010-04-30	
2010-05-25	
2010-10-25	
2011-08-02	

* ICSS(K-1) and ICSS(K-2) indicate Kappa-1 and Kappa-2 process. The results of Algorithm ICSS Inclan Tiao (IT) are not included in Table VI.

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According to Table 6, dummy variable for structural breaks in conditional variance are used to estimate FIGARCH model. The results of estimation with dummy variable of FIGARCH model are presented Table 7.

TABLE VII: The Results of FIGARCH Model With Dummy Variable

p=1,q=1	FIGARCH	
	N	SST
ω	0.268689** (0.073385) [0.0003]	0.272860** (0.070303) [0.0001]
D(dummy)	-1.709816** (0.086034) [0.0000]	-1.710550** (0.079800) [0.0000]
β_0	0.117883*** (0.072445) [0.1037]	0.124996*** (0.075008) [0.0957]
β_1	0.345038** (0.083091) [0.0000]	0.355219** (0.084509) [0.0000]
d	0.340904** (0.029425) [0.0000]	0.347702** (0.027468) [0.0000]
v		6.320736** (0.43955) [0.0000]
ln(ζ)		-0.039916** (0.013849) [0.0040]

Log(L)	**-14584.282**	**-14409.483**
AIC	**4.434432**	**4.381910**
SIC	**4.439593**	**4.389135**
Çarpıklık	**-0.24672**	**-0.24712**
Aşırı Basıklık	**2.1678**	**2.1712**
J-B	**1355.1**	**1359.4**
Q(5)	**57.7956****	**57.7507****
Q(10)	**71.0991****	**71.1047****
Q(20)	**83.8609****	**83.8647****
Q(50)	**114.318****	**114.345****
$Q^2(5)$	**1.78241**	**1.50565**
$Q^2(10)$	**6.63621**	**6.40864**
$Q^2(20)$	**12.1658**	**11.9284**
$Q^2(50)$	**45.5347**	**45.3487**
ARCH(5)	**0.38409[0.8600]**	**0.32790 [0.8964]**
ARCH(10)	**0.66898[0.7543]**	**0.64714 [0.7742]**
P(40)	**643.4164**	**480.2796**
P(50)	**790.2584**	**618.9210**
P(60)	**953.1733**	**742.3891**

****, *** indicate statistically significant 5% and 10% respectively. ( ) indicates standard error,**

[ ] indicates p-values. P(40), P(50) ve P(60) indicate , Pearson Goodness of Fit for 40, 50, 60 cells.

According to Table 7, dummy parameter (D) for structural breaks is statistically significant. Furthermore, the values of long memory parameter d of FIGARCH model with dummy are not very different from model parameters in Table III. Consequently, it can be said that structural changes don't affect long memory property in conditional variance of returns. In other words, long memory property in Turkey Stock Market returns don't be affected by structural breaks in conditional variance of returns.

III. CONCLUSIONS

The study evaluates long memory property, asymmetric effects and structural changes in volatility of Turkey Stock Market for the period of 01.02.1990-24.03.2015. For this purpose, FIGARCH, FIEGARCH and FIAPARCH models for long memory in volatility of returns are estimated. Furthermore, structural changes in volatility are tested by using algorithms of ICSS [23], ICSS(Kappa-1) and ICSS(Kappa-2) developed by [24]. Consequently, the findings approve that there is long memory property in volatility of Turkey Stock Market. This predictable structure of volatility indicates that Turkey Stock Market is inefficient market. Moreover, the effects of shocks on the volatility are asymmetric. In other words, negative shocks (bad-news) affect volatility more than positive shocks (good-news). Finally, structural changes in volatility for the period of 1990-2015 are not statistically significant on long memory in volatility of returns. The results of study present important findings for investors, policy-makers, financial analysists and academicians.

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