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Research Article

Long Memory Properties in Return and Volatility: An Application of the Impact of Arab Spring in Turkey Financial Market

[1]Pinar Cevik and [2]Hamdi Emec
[1]Surveillance Department, Turkish Derivatives Exchange, Izmir, Turkey
[2]Departments of Econometrics, Dokuz Eylul University, Izmir, Turkey

Abstract: The Arab Spring which began on 17 December 2010 with the civil rebellions, revolutionary wave of demonstrations and protests in the Tunisia, Egypt, Libya, Yemen, Bahrain and Syria. The Arab Spring not only created a domino effect between Arabic countries but also it reflected a significant influence on the financial markets all over the world. The objective of this study is to analyze the impact of the Arab Spring in Turkey Financial Market in consideration of long memory. Long memory can be defined as the persistence of the unexpected shocks on the underlying has long lasting effects. Modeling long memory in stock returns and volatility has also attracted great deal of attention from finance literature recently. Existence of long memory is determined both for the returns and volatility of the time series by using different methods. Existence of long memory can be tested by Rescaled Range Statistics (R/S), Geweke and Porter-Hudak (GPH) Model and Gaussian Semi Parametric (GSP) Method. In consequence of these tests, if the stock returns have long memory affect then respectively Fractionally Integrated Autoregressive Moving Average Model (ARFIMA) and the Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity (FIGARCH) model are used to detect the long memory in respectively return and volatility. In this study, the impact of the Arab Spring is investigated by modeled the long memory in Istanbul Stock Exchange using ISE 30 index prices in between December 17, 2010 and April 02, 2012.

Keywords: ARFIMA, FIGARCH, GPH model, GSP method, long memory, R/S statistics

INTRODUCTION

The Arab Spring began on 18 December 2010 in Tunisia by Muhammed Bouzazi who set himself on fire (Ayhan, 2012), against unemployment, insufficient food source, inflation, political corruption, subjection of freedom of expression, irregularities and adverse living conditions in conjection with imposed repressive and authoritarian regime. The Arab Spring spreaded to other Arabic countries by generating the domino effect (Dogan, 2012).

The domestic authority of Arab countries like Tunisia, Egypt, Syria, Bahrain, Algeria, Jordan (Barari, 2012), Yemen, Mauritania, Saudi Arabia, Oman, Iraq, Lebanon and Fas tried to suppress the revolt by military power against to the civilians. Due to the World public opinion, NATO and United Nations organization are not unconcerned to civil war; they acted prudently and performed the operations (Dogan, 2012; Gülriz, 2012; Yılmaz, 2012).

The domino effect of Arab Spring leaves an indelible impression not only the world public opinion and external media but also Turkish media and foreign politics of Turkey. Gülriz (2012) and Kibaroğlu (2011). Comments of the authorities about the foreign policy of the Turkey related to Arab Spring (Yılmaz, 2012) caused rebounds in Turkey Financial market (Kibaroğlu, 2011) in addition, it is observed that the market is adversely affected from the news related evolving revolution into civil war and rising mass murders towards civilians and affected positively fall of Egypt government and conciliatory gestures of the authorities and threatening behavior of the world public opinion to the Arabic authorities

This study aims to investigate whether Turkish capital Market is affected by the political and diplomatic decisions and stances of Turkey that is Islamic government and neighbor to the some Islamic countries where is experienced the revolutions and civil war and as a part of Arab Spring and whether the effects continues long or short term. With in this context, ISE 30 index session data is used to determine whether the data contains the long memory effect by testing and construction model.

METHODOLOGY

There are many papers related to existence of the long memory on the financial dataset. Hiemstra (1997) concludes that there is some evidence consistent with persistent long memory in the returns of a small

Corresponding Author: Pinar Cevik, Surveillance Department, Turkish Derivatives Exchange, Izmir, Turkey

proportion of stocks also long memory is not a widespread characteristic of stock market. There are some investigations which search long memory existence other economic indicators (Hwang, 2001) applied the asymmetric long memory (Fractionally Integrated Family Generalized Autoregressive Conditional Heteroskedasticity) FIFGARCH model to the exchange rate returns. Tang and Shieh (2005) applied FIGARCH and HYGARCH models to investigate long memory of stock index futures markets.

Besides the many studies that examine long memory in stock returns, long memory in volatility has also attracted great deal of attention from finance literature. Christensen and Nielsen (2008) introduced FIEGARCH-in-mean model to avoid long memory property of volatility. Moreover, Kasman (2007) investigate the dual long memory property in the Turkish stock market and modeled long memory in the returns and volatility by using ARFIMA-FIGARCH. Kang and Yoon (2007), Liu (2000) and Korkmaz (2009) investigate the long memory in return and volatility for various financial markets.

The long memory existence in the dataset is able to test by R/S statistics, Geweke and Porter-Hudak (GPH) Model and Gaussian Semi Parametric (GSP) Method.

Rescaled Range (R/S) statistics: One of the oldest and best known methods to decide whether long memory exist or not is rescaled range (R/S) statistics which was introduced by Mandelbrot and Wallis (1969) and Hurst (1951). By using R/S statistics self-similarity parameter (H) which measures the intensity of long-range dependence in a time series can be calculated.

Lo (1991) provides many references and a rigorous description of appropriate tests when the preferred alternative to randomness is long-term dependence. The range defined by a set of returns $\{y_1, y_2, \ldots .. y_p\}$:

$$M_p = \left[\max_{1\le T\le p} \sum_{t=1}^{T} (r\, y_t - \bar{y})\right] - \left[\min_{1\le T\le p} \sum_{t=1}^{T} (y_t - \bar{y})\right]$$

where, $\bar{y}$ is the mean of set of returns $\{y_1, y_2, \ldots .. y_p\}$. R/S-test statistics are ranges divided by scaled standard deviations:

$$\frac{R}{S} = \frac{1}{\sqrt{n}\sigma} M_p$$

Mandelbrot (1972) was defined test statistics as: $\sigma = s$ defines $(R/S)_{Man}$ and Lo (1991) defined test statistics as:

$$\sigma^2 = s^2\left[1 + 2\sum_{j}^{q}\left(1 - \frac{j}{q+1}\right)\tilde{\rho}_j\right] \text{defines } (R/S)_{Lo}$$

with s^2 the sample variance of returns.

The null hypothesis of Mandelbrot is "there is no autocorrelation". However, the null hypothesis of Lo is "there is no long-term dependence".

Geweke and Porter-Hudak (GPH) model: Geweke and Porter-Hudak (1983) proposed a semi-nonparametric approach to testing long memory in terms of fractionally integrated process. Moreover, Geweke and Porter-Hudak (1983) used Fourier transformation and spectral density into the following formula:

$$\ln f(w_i) = \beta - d\ln\left[4\sin^2\left(\frac{w_j}{2}\right)\right] + e_j$$

for j = 1, 2,…, n_f (T). They used periodogram estimate of $f(w_i)$ and least square to estimate $\check{d}$ from the above function which is normally distributed in large samples. Then, the test statistics (t-statistics) defines as following:

$$t_{d=0} = \check{d}\left(\frac{\pi^2}{6\sum_{j=1}^{n_f}(U_j - \bar{U})^2}\right)^{-1/2}$$

where,

$U_j = \ln\left(4\sin^2\left(\frac{w_j}{2}\right)\right)$

$\bar{U}$ = The sample mean of U_j for j = 1, 2,…, n_f(T)

Null hypothesis of the GPH is "there is no long memory (d = 0)".

Gaussian Semi Parametric (GSP) method: Gaussian Semi Parametric estimation model which is introduced by Robinson and Henry (1999) is a generalization of Whittle approach. GSM which is based on the specification of the shape of the spectral density of the time series, usually applied for semi parametric data.

Assume that y_t is a stationary process with spectral density satisfying:

$$f(\varphi) \sim A\varphi^{1-2B}$$

as φ converges to 0 from the right side with $A \epsilon (0, \infty)$ and $B \epsilon (0,1)$. G and H correspond to $\frac{\sigma^2\theta(1)^2}{2\pi\emptyset(1)^2}$ and 0.5 + d, respectively:

$$G(A, B) = \frac{1}{k}\sum_{i=1}^{k}\left[\log A\varphi_i^{1-2B} + \frac{\varphi_i^{-(1-2B)}}{A} I(\varphi_i)\right]$$

where, k<0.5 n also m is integer.

ARFIMA model: Granger and Joyeux (1980) and Hosking (1981) introduced the ARFIMA as a popular parametric approach to test the long memory property in the asset returns. Denoting L as the lag operator and replacing the difference operator (1-L) of an ARIMA process with the fractional difference operator $(1\text{-}L)^d$ where d denotes the degree of fractional integration. The ARFIMA (p, d, q) process can be expressed as:

$$\Phi(L)(1-L)^{\omega}(y_t-\mu)=\Gamma(L)_{\varepsilon_t}$$

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

where,
μ : The unconditional mean
ε_t : Independently and identically distributed (i.i.d.) error term

AR and MA lag polynomials with standing outside the unit root as follows:

$$\Phi\,(L)=1-\Phi_1L_1-\Phi_2L_2-\ldots-\Phi_pL_p\text{ve}$$

$$\Gamma\,(L)=1+\gamma_1L+\gamma_2L_2+\ldots+\gamma_qL_q$$

The most important difference between ARIMA and ARFIMA model is the characteristics of the differencing parameter d which is defined an integer in ARIMA model and defined a range in ARFIMA model.

The long range properties of series depend on the value of d. For d∈ (0, 0.5) the autocorrelations are all positive. They decay hyperbolically to zero as the lag length increases, compared to the usual exponential decay in the case of stationary ARMA model with $\xi = 0$. For d∈ (-0.5, 0), the series is said to exhibit intermediate memory. In this case the autocorrelations are all negative and decay hyperbolically to zero. For d∈ (-0.5, 0.5), the series is stationary and invertible. However, for d = 1, the series follows a unit root process.

Fractionally Integrated GARCH (FIGARCH) model: Baillie (1996) introduced FIGARCH model as a popular parametric approach to test the long memory property in the volatility of financial return series. In contrast to an stationary time series in which shocks die out at an exponential rate, or a non-stationary time series in which there is no mean reversion, shocks to an I(d) time series with d∈ (0, 1) decay at a very slow hyperbolic rate. The FIGARCH (p, d, q) model is given by:

$$\varphi(L)(1-L)^d\varepsilon_t^2=\alpha+[1-\beta(L)]\omega_t$$

Conditional variance of ε_t is:

$$\sigma_t^2=\frac{\alpha}{[1-\beta(1)]}+\gamma(L)\varepsilon_t^2$$

where, $\gamma(L)=\gamma_1L_1+\gamma_2L_2\ldots\gamma_kL_k$

When 0<d<1, the coefficients capture the short term dynamics of volatility while fractional difference parameter d models the long term characteristics of volatility.

FIGARCH model is the extension of IGARCH model in which shocks to the conditional variance are completely persistent and therefore the unconditional variance does not exist. In addition, when d = 0, FIGARCH process gives the same output with GARCH process and when d = 1, FIGARCH process gives the same output with IGARCH process.

BBM estimation: BBM estimation method is proposed by Baillie *et al*. (1996) is to model persistent volatility and incorporate the idea of long memory fractional differencing into the GARCH (Generalized Autoregressive Conditional Heteroskedastic) model. FIGARCH (p, d, q) model by BBM is:

$$\varphi(L)(1-L)^d\varepsilon_t^2=\alpha+[1+\beta(L)]v_t$$

where,
$\varphi(L)=1-\sum_{i=1}^{p}\varphi_i\,L^i$
$(L)=\sum_{i=1}^{q}\beta_iL^i$
L = The lag operator

Chung estimation: Chung estimation model is proposed by Chung (1999) with the aim of pointing up some little drawbacks in the BBM model. Chung constructed a slightly different process:

$$\varphi(L)(1-L)^d(\varepsilon_t^2-\sigma^2)=[1-\beta(L)](\varepsilon_t^2-\sigma_t^2)$$

where, the unconditional variance of ε_t is σ^2.

APPLICATION

In application, session data of ISE 30 index in between 17 December 2010 and 02 April 2012 are used. Due to the trend in index values, the logarithms of index values are used in the analysis to remove the trend in the dataset. The descriptive statistics are reported in Table 1.

According to the descriptive statistics and Jarque-Bera (JB) normality test, data do not correspond with the normal distribution assumption and there are significant departures from normality. Moreover, time series are positively skewed and leptokurtic. In order to test the hypothesis of independence, Ljung-Box (Q) statistics is estimated for the time series and squared data which are presented in Table 2. From the test statistics, the null of white noise is rejected and assert that these logarithmic time series are autocorrelated.

Before testing the long memory in logarithmic series and volatility, these series need to be stationary. The unit root tests are used for stochastic trends in the autoregressive representation of logarithmic series. The

Table 1: The descriptive statistics

Mean	S.D.	Min.	Max.	Skewness	Kurtosis	Jarque Bera	Sample size
0.0099002	0.043021	-0.38696	0.69315	8.0271*	129.72*	466270*	655

*: Denotes the statistic is significant at 1% level; JB test statistic has a chi-squared distribution with 2 degrees of freedom; S.D.: Standard deviation; Min.: Minimum; Max.: Maximum

Table 2: Ljung-box (Q) statistics

	Q statistics	Probability		Q^s statistics	Probability
Q (5)	381.268	0.0000	Q (5)	129.881	0.0000
Q (10)	505.672	0.0000	Q (10)	132.299	0.0000
Q (20)	603.276	0.0000	Q (20)	132.723	0.0000
Q (50)	680.560	0.0000	Q (50)	132.755	0.0000

p value denotes the probability value which indicates the significance at 1% level; Q (20) and Q^s (20) are the Ljung-box statistic for returns and squared returns, respectively

Table 3: The unit root tests

KPSS test			ADF test		
Test statistics	2.9139		Test statistics	-17.4691	
	1%	0.739		1%	-2.56572
	5%	0.463		5%	-1.94093
	10%	0.347		10%	-1.61663

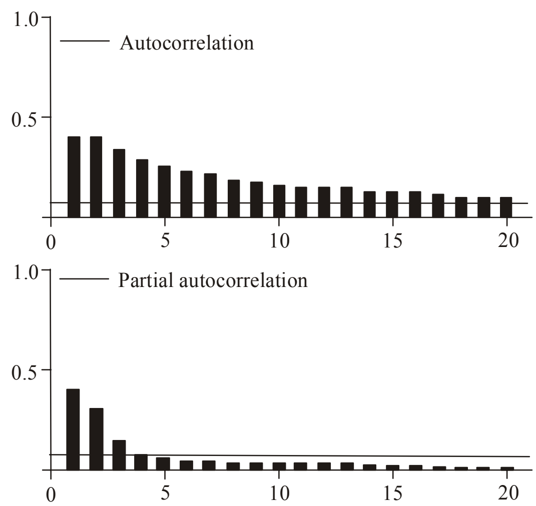

Fig. 1: ACF and PACF graphics of log price series

KPSS and ADF tests are used to check whether the series are stationary or not. Table 3 reports the results of the KPSS and ADF tests for the logarithmic series.

The KPSS test statistics indicate that data is significant to reject the null hypothesis of stationary, suggesting that it is non-stationary processes. In addition, the ADF test statistics reveal that the data is stationary since it rejects the null hypothesis. Usually these tests give the same solution for financial time series, however, for the data which is affected from the external factors like electricity prices, as mentioned in many research papers these tests may also give the adverse solutions since the effects of the long memory. Kuswanto and Salamah (2009) applied regime switching long memory model to German Stock Returns, they mentioned in their study that, KPSS test tends fail to reject the alternative of unit root process, when the real process is long memory. Moreover, Lee and Schmidt (1996) showed that other unit root test should be applied to the data which contains long memory. In the Fig. 1, the ACF and PACF graphs of the logarithmic data are presented.

Test statistics of Hurst-Mandelbrot R/S, Lo R/S, GPH and GSP which is used to confirm the existence of the long memory effect on the dataset are presented in the Table 4.

In 99% critical interval, the null hypothesis for Hurst-Mandelbrot R/S and Lo R/S statistics are rejected. So this is a fact that the log values exhibits the long memory effects. In addition, due to the d parameter is contained from (0, 0.5) interval and it is statistically significant, this shows that the generated series have the long memory effect. ARFIMA model is used to analyze the long memory in time series. In the Table 5 the estimation results of ARFIMA (p, d, q) model are presented for different p, d, q values.

In the Table 5, different specifications of the ARFIMA (p, d, q) with (p, q) ϵ (0, 1, 2) are estimated by using maximum likelihood method. Since, d-ARFIMA coefficient is stationary, invertible and also statistically significant in 99% confidence interval for all estimated models, the generated series contains long memory. All of the ARFIMA models reveal that they do not correspond with the normal distribution assumption since the Jarque-Bera (JB) statistics shows significant departures from normality. In ARFIMA (1, d, 1) is exhibited intermediate memory. Autocorrelation is negative and decay hyperbolically to zero, since dϵ (0, 0.5). In ARFIMA (2, d, 1), ARFIMA (1, d, 2) and ARFIMA (3, d, 1) models, autocorrelation is positive and decay hyperbolically to zero as the lag length increases since dϵ (0, 0.5). The best performed ARFIMA (p, d, q) model is determined considering minimum AIC, significant AR and MA coefficients and maximum log likelihood value. As a result of that, ARFIMA (1, d, 2) model is the best performed model.

Portmanteau tests goodness of fit the model especially for ARIMA models. As seen in the Table 5, Portmantetau test statistic is significant for all ARFIMA test in 99% confidence interval. Due to the fact that, the autocorrelation coefficients up to lag 25 are different from zero.

When Residual Sum of Squares (RSS) which is a measure of the discrepancy between the data and

Table 4: Long memory tests

	Hurst-mandelbrot R/S	Lo R/S	GPH	GSP
d parameter	-	-	0.388047 (0.0407224)	0.268399 (0.0276501)
Test statistics	3.28996	2.78836	-	-
Table values	Table values		Probability	Probability
90%	[0.861, 1.747]		[0.0000]	[0.0000]
95%	[0.809, 1.862]			
99%	[0.721, 2.098]			

Table 5: Estimated ARFIMA models

	ARFIMA (1, d, 1)	ARFIMA (2, d, 1)	ARFIMA (1, d, 2)	ARFIMA (3, d, 1)
d-ARFIMA	0.496552*	0.299367*	0.479669*	0.449910*
	(0.004851)	(0.08498)	(0.02778)	(0.05984)
AR (1)	-0.453208*	0.560492*	0.994019*	0.318621*
	(0.09839)	(0.04840)	(0.005743)	(0.05778)
AR (2)	-	0.434247*	-	0.405632*
		(0.04768)		(0.04062)
AR (3)	-	-	-	0.266278*
				(0.05163)
MA (1)	0.183726	-0.665399*	-1.39377*	-0.624819*
	(0.1077)***	(0.06683)	(0.04928)	(0.06296)
MA (2)	-	-	0.663269*	-
			(0.04151)	
Constant	0.0333287	0.321737	0.679364	0.507874
	(0.1785)	(0.5045)	(3.263)	(1.556)
AIC	-3.96746756	-4.11478703	-4.18609685	-4.14361016
AIC.T	-2598.69125	-2695.1855	-2741.89344	-2714.06465
Portmanteau (25)	341.59*	28.190	65.118*	20.610
ARCH (1)	224.98*	279.43*	314.71*	304.98*
RSS	0.0607746	0.0560575	0.0407271	0.0490587
Mean	-0.0077469	-0.0015009	-0.00046943	-0.00081267
Std	0.031969	0.030444	0.029300	0.029930
Skewness	0.78978	-0.32764	-0.57917	-0.87868
Excess kurtosis	118.41	140.51	123.30	135.24
Asymptotic test	382690*	538830*	414970	499210
Normality test	9172.5*	10366*	9399.5*	10426*
Log likelihood	1304.34562	1353.59275	1376.94672	1364.03233

Maximum likelihood estimated standard errors are reported in the parentheses below corresponding parameter estimates. The ARCH (1) denotes the ARCH test statistic with lag 1; The mean, standard deviation, skewness and kurtosis are also based on standardized residuals; *: Denotes significance levels at the 1%

estimated models, decreases, fitting of the model increases. The smallest RSS is shown in the output of ARFIMA (1, d, 2).

The standardized residuals display skewness and excess kurtosis. Furthermore, the relatively large value of kurtosis statistics implies that the residuals appear tobe leptokurtic, or fat-tailed and sharply peaked about the mean when compared with the normal distribution.

ARCH LM (1, 1) test statistics of the generated time series are significant in 99% confidence interval for all ARFIMA models in the Table 5. So, there is ARCH effect in the standardized residuals, which indicates that there is also conditional heteroscedasticity. Moreover, asymptotic test is another measure of heteroscedasticity. According to its statistics, in 99% confidence interval the null hypothesis which is the series has homoscedasticity, is rejected. In the purpose of obtaining homoscedasticity, GARCH models estimation is required.

Estimated models with different orders with skewed t distribution are compared in the Table 6. d-ARFIMA and d-FIGARCH coefficients are statistically significant in 99% confidence interval for all models, which implies the existence of long memory in both transformed electricity prices and its variances.

GARCH (β1) and GARCH (β2) coefficients are statistically significant and low, which indicates that a weak autoregressive component in the conditional variance process.

The skewed student-t distribution is found to outperform the normal distribution and student t distribution since the t-statistics of the parameter Student DF is significant in 99% confidence interval for both BBM and Chung estimation methods. Moreover, the asymmetric parameters Asymmetry are insignificant and are not different from zero for both BBM and Chung estimation methods. This suggests that ARFIMA-FIGARCH models the densities of generated log electricity price series are not skewed. Furthermore, the higher values of Pearson (50) test statistics reconfirm the lack of skewed Student-t distribution for both BBM and Chung estimation methods.

AIC, SW, SB, H-Quinn and Q statistics are the vital statistics which indicate the best performed model. In between ARFIMA-FIGARCH models with different estimation methods and distributions, ARFIMA (1, 1, 2) -FIGARCH (1, 0.999861, 1) which is estimated by using Chung method is found the outperformed model since it has minimum AIC, SW, SB, H-Quinn criteria and significant Q (50) statistics.

Table 6: Constructed ARFIMA-FIGARCH models

	ARFIMA (1, d, 2) FIGARCH (2, d, 1)	ARFIMA (1 ,d, 2) FIGARCH (1, d, 1)	ARFIMA (2, d, 1) FIGARCH (1, d, 1)	ARFIMA (3, d, 1) FIGARCH (1, d, 2)
Estimation method	CHUNG	CHUNG	BBM	BBM
Cst (M)	-0.059063*	0.002827	0.017948	-0.110697*
	(0.00053447)	(0.0014291)	(0.010222)	(5.8444e-007)
d-ARFIMA	-0.928379*	1.000000*	0.595887*	0.410714*
	(0.0010794)	(0.00049)	(0.016112)	(4.1260e-005)
AR (1)	0.561226	0.614928*	0.108025*	0.006529*
	(0.0012950)	(0.0288)	(0.010266)	(3.9699e-005)
AR (2)	-	-	0.467686*	0.353726*
			(0.033544)	(0.0010325)
AR (3)	-	-	-	0.328624*
				(0.0010649)
MA (1)	0.317972*	0.440192*	-0.523985*	0.369810*
	(0.0029988)	(0.1191)	(0.0011717)	(2.9293e-006)
MA (2)	0.284492*	0.435341*	-	-
	(1.4842e-005)	(0.0342)		
Cst (V)	0.100545*	0.003685	0.016618*	0.020489*
	(0.0033124)	(0.046922)	(0.00095456)	(9.9508e-005)
d-FIGARCH	0.994354*	0.999861*	0.897927*	0.713851*
	(0.00031454)	(2.3189e-006)	(0.0037428)	(1.9214e-005)
ARCH (1)	0.835621*	0.576784*	0.841368*	0.309584*
	(3.6872e-005)	(0.10602)	(2.3099e-005)	(1.7182e-005)
ARCH (2)	-	-	-	0.258739*
				(2.7280e-005)
GARCH (β1)	0.297792*	0.574380*	0.070083**	0.477490*
	(2.9746e-005)	(0.10278)	(0.034200)	(2.5667e-005)
GARCH (β2)	0.143732*	-	-	-
	(5.2986e-005)			
Asymmetry	-2.082346*	0.702295*	1.809298*	-10.185545*
	(0.21774)	(0.083834)	(0.16169)	(1.4675)
Tail	2.059749*	2.644286*	2.704587*	4.054256*
	(0.0016633)	(0.15939)	(0.10080)	(6.5343e-005)
Mean	0.00990	0.00990	0.00990	0.00990
Variance	0.00185	0.00185	0.00185	0.00185
Skewness	8.02712	8.02712	8.02712	8.02712
Kurtosis	132.71925	132.71925	132.71925	132.71925
Log-likelihood	5985.59	6787.144	3453.08	3117.78
AIC	-18.239975	-20.690516	-10.510183	-9.480233
SW	-18.157813	-20.691068	-10.434868	-9.391225
SB	-18.240630	-20.615201	-10.510735	-9.48100
H-quinn	-18.208117	-20.661313	-10.480980	-9.445721
JB	9.4839e+006	1.0961e+007	5.8301e+006	1.1324e+007
Pearson (50)	684.0076*	1288.8931*	1608.1298*	5751.3359*

Standard errors are reported in the parentheses below corresponding parameter estimates; P (50) is the Pearson goodness-of-fit statistic for 50 cells; The Q (50) and Q^s (50) are the Ljung-box test statistics with 50 degrees of freedom based on the standardized residuals and squared residuals, respectively; *: Indicate significance levels at 1%

CONCLUSION

In this study, effect of the Arab Spring on the ISE 30 session returns is investigated in between 17 December 2010 and 02 April 2012.

Foreign policy, precautions, cross-border operations, international reliefs of Turkey related to Arab Spring reflected to Turkey financial market that can be interpreted from the financial market response. The main purpose of this study is to investigate persistence of the unexpected shocks on the Turkey financial market and long lasting effects of Arab Spring. In application, the presence of long memory in ISE 30 returns is tested and the best fitted model is constructed which is ARFIMA (1, 1, 2) -FIGARCH (1, 0.999861, 1) by using Chung model with student t distribution. Eventually, presence of long memory shows that Turkey financial market does not immediately respond to Arab Spring, but reacts to it gradually over time. The means of constructed model is statistically significant implies that the effects of the any shock on the ISE 30 returns and volatility are persistent and vanish very slowly into the long term. This is a great change to forecast the ISE 30 returns for the short run. Hence, the possibility of consistent speculative profits may arise because of the presence of long memory in ISE 30 returns, contradicting the weak form market efficiency hypothesis, which states that past returns cannot predict future returns.

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