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Long Memory in the Turkish Stock Market Return and Volatility

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Abstract:

This paper examines the dual long memory property of the Turkish stock market. The data set consists of daily returns, and long memory tests are carried out both for the returns and volatility. The results indicate that long memory dynamics in the returns and volatility might be modeled by using the ARFIMA-FIGARCH model. The results of the ARFIMA-FIGARCH model show strong evidence of long memory in both returns and volatility. The long memory in returns implies that stock prices follow a predictable behavior, which is inconsistent with the efficient market hypothesis. 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.

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1. Introduction

The potential presence of long memory in financial time series has been one of the popular research topics in finance in recent years. Long memory in financial time series can be defined as the existence of dependencies among observations due to hyperbolically decaying autocorrelation function. Technically, a long memory process can be characterized by a fractionally integrated process (i.e. the degree of integration is less than one but greater than zero). Hence, the impacts of a shock persist over a long period of time.

The fractionally integrated autoregressive moving average (ARFIMA hereafter) model proposed by Granger and Joyeux (1980) and Hosking (1981) tests the long memory property in financial return series. The ARFIMA model allows the integration order of the conventional ARMA model to take non-integer value between 0 and 1. A vast literature has focused on investigating long memory in returns using the ARFIMA models. The empirical results of studies applying long-memory estimation to financial series of varying frequencies and across range of international markets have produced mixed results. Several studies have reported favorable evidence of long memory dynamics for emerging markets (see for example Sadique and Silvapulle, 2001; Henry, 2002; Gil-Alana, 2006; Kilic, 2004; Assaf and Cavalcante, 2005). However, a number studies on the developed markets have reported evidence against long-memory (see for example, Lo, 1991; Crato, 1994; Cheung and Lai, 1995; Barkoulas and Baum, 1996; Jacobsen, 1996; Tolvi, 2003).[1]

Modeling long memory in volatility has also attracted great deal of attention from finance literature recently. To detect the memory pattern in volatility, Ballie *et al.* (1996) proposed the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH hereafter) model by extending the IGARCH model, which is a special case of the GARCH model, through allowing for persistence in the conditional variance. The infinite persistence implied by the IGARCH model appears too restrictive and seems contrary to empirical evidence. It is shown that GARCH and IGARCH models have memory which is much shorter than that of generally financial series have. The FIGARCH process provides an additional flexibility aiming at capturing long memory in volatility. The important practical difference between a GARCH process and a FIGARCH process is that for

[1] These mixed empirical results are expected since long memory provides evidence against weak-form market efficiency. The developed markets are expected to be more efficient than emerging markets.

the former shocks die out at a quick exponential rate, while for the latter shocks die out at a slower hyperbolic rate.

A number of studies have investigated the long memory property of volatility using data from developed markets. The general finding is that daily stock returns are approximately martingale with long memory in conditional volatility process.[2] Despite the vast literature that analyses the long memory properties of mature stock markets, there is little research has been done on the time properties of emerging markets.[3] The results of these studies indicate the existence of long memory in both stock returns and volatility.[4]

The objective of this paper is to provide additional information on the presence of long memory in stock returns and volatility, using data from an emerging stock market, namely the Istanbul Stock Exchange (ISE). We estimate ARFIMA-FIGARCH models to explain the presence of long memory in stock returns and volatility. In contrast to the mature markets that are highly efficient with respect to the speed of information reaching traders, investors in emerging markets may tend to react slowly and gradually to new information. Due to the common features of emerging markets such as higher and persistent volatility, market thinness, nonsyncronous trading, rapid changes in regulatory framework, and unpredictable market response to information flow, stock returns in emerging markets behave differently and have distinct properties compared to mature markets. Hence, modeling the long memory in return and volatility has become an integral part of risk measurement and investment analysis in these markets.

The rest of the paper is organized as follows: Section 2 provides brief information on the stock market in Turkey. The methodology is presented in Section 3. Section 4 gives information about the data and reports the empirical results. Section 5 is devoted to conclusions.

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[2] See for example, Li (2002), Vilasuso (2002), Andersen, *et al*. (2001), Pong, *et al*. (2004), Martens and Zein (2004), Martens, *et al*. (2004), and Bhardwaj and Swanson (2006).

[3] See for example, Kilic (2004), Vougas (2004), Floros, *et al*. (2007), Kang and Yoon (2007).

[4] Long memory in asset returns affects the efficiency of the market in pricing securities. If asset returns exhibit long memory then the observations have a predictable component and therefore, past asset returns could be used to predict future returns. Hence, long memory provides evidence against weak-form market efficiency, which states that past returns cannot predict future returns. Long memory in volatility, however, shows that uncertainty or risk is an important determinant of the behavior of stock data. The volatility as a measure of risk is the only quantity concerning the stock having an influence on the price of a stock option. The possibility of long-term forecasts of the squared returns would result in a different valuation of the option. This would allow arbitrage. Hence the question whether volatilities do or do not exhibit long-range dependence is of strong consequences for evaluating stock options.

2. Stock Market in Turkey

Turkey is integrated with the world capital markets via the establishment of the Turkey Stock Exchange (ISE hereafter) in 1986. The ISE is the fifth largest exchange in terms of total value of bonds traded (about $405 billion) in 2006. Turkey had the Gross Domestic Product (GDP hereafter) of $402.71 billion with the growth rate of 6.10% in 2006. Market capitalization of the Turkish stock market was around $162 billion corresponding 40% of the GDP in 2006. The domestic market capitalization increases 172% since 1986. The number of listed companies reaches 316 in the ISE with the increase of 295% since 1986. Moreover, the 15 newly listed companies contribute about $4.1 million to the market capitalization in 2006. Investment inflow via initial and secondary public offerings reaches $861.5 million.

The ISE is the tenth fastest growing emerging stock exchange in terms of the market capitalization in 2007. Also performance of broad market indices increases around 42%, leading the ISE to be the tenth best performing exchange among the WFE (World Federation of Exchanges) members and the fifth best performing exchange in Europe region.

The capital account liberalization in 1989, which opens stock market to foreign investors through no restrictions on trading and repatriation of capital and profits, along with fully convertible currency policy, makes the ISE not only an attractive investment alternative, but also sensitive to capital movements and shocks resulting from news on macroeconomic data, global crises, and economic and political developments in Turkey. Due to convenient investment environment, the share of foreign investors in the ISE reached 70% in 2007. However, volatility in the ISE increased significantly after the capital account liberalization of 1989. Global and domestic financial crises (1994, 1997, 1998, 2000 and 2001) had devastating influences on the ISE. Hence, modelling volatility is critical for global investors in terms of portfolio diversification and other risk management strategies.

3. Methodology

In this section, we discuss the methods that will be used in this study. A stationary stochastic process is defined a long memory process if the autocorrelations are positive and decay monotonically and hyperbolically to zero. Using the ARFIMA-FIGARCH modeling technique we test for the presence of long memory in the daily returns and volatility of the Turkish stock market.

ARFIMA Model

The ARFIMA model, which is commonly used parametric approach for testing the long memory property in the financial return series, developed by Granger and Joyeux (1980) and Hosking (1981). The model considers the fractionally integrated process I(*d*) in the conditional mean. The ARFIMA(*p*, ξ ,*q*) for a time series process y_t can be expressed as follows:

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

$$\varepsilon_t = z_t\sigma_t, \qquad z_t \sim N(0,1) \tag{2}$$

where ξ is the fractional difference parameter, *L* is a lag operator, $\phi(L)$ and $\theta(L)$ are polynomials in the lag operator of orders *p* and *q*, respectively and ε_t is independently and identically distributed with a variance, σ^2. Long memory arises through the fractional differencing parameter, ξ, which is allowed to assume any real value. Following Hosking (1981), when $\xi \in (-0.5, 0.5)$, 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. When $\xi = 0$, the process is stationary, and the effect of shocks of ε_t on y_t decays geometrically. When $\xi \in (0, 0.5)$, the autocorrelations are positive and decay hyperbolically to zero, implying long memory. When $\xi \in (-0.5, 0)$, then the process is identified as having intermediate memory, since autocorrelations are always negative. However, for $\xi = 1$, the series follows a unit root process.[5]

FIGARCH Model

Baillie *et al*. (1996) introduced long memory in the conditional variance of a GARCH model and proposed the fractionally integrated GARCH, or FIGARCH (*p,d,q*) model, where the conditional variance can be expressed as follows:

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

Where $v_t \equiv \varepsilon_t^2 - \sigma_t^2$. The v_t process can be interpreted as the innovations for the conditional variance and has zero mean serially uncorrelated. To ensure covariance stationarity the roots of $\phi(L)$ and $[1-\beta(L)]$ are constrained to lie outside the unit circle. The FIGARCH model offers greater flexibility for modeling the conditional variance. The FIGARCH model in Eq. (3) reduces to a GARCH model when $d = 0$ and to an IGARCH model when $d = 1$. The FIGARCH(*p,d,q*) model

[5] See Baillie *et al*. (1996) for more details.

imposes an ARFIMA structure on ε_t^2. The FIGARCH model in Eq. (3) can be rewritten as follows:

$$[1-\beta(L)]\sigma_t^2 = \omega + \left[1-\beta(L)-\phi(L)(1-L)^d\right]\varepsilon_t^2 \tag{4}$$

or equivalently,

$$\sigma_t^2 = \frac{\omega}{[1-\beta(1)]} + \lambda(L)\varepsilon_t^2 \tag{5}$$

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

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 $0 \le d < 1$. 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.

4. Data and Empirical Results

Data

The FIGARCH model is estimated with daily data for the period 1988-2007. The returns are defined as the continuously compounded percentage rate of return at time *t*, $r_t = \ln(p_t / p_{t-1})$, where p_t is the stock market index. The analysis is based on daily ISE-100 index. The data is obtained from the electronic data delivery system of the Central Bank of the Republic of Turkey.

The summary statistics are reported in Table 1. The return series exhibits the usual characteristics of a small mean dominated by a large standard deviation and reveals that it does not correspond with the normal distribution assumption of normality. Employing the Jarque-Bera (*JB*) statistics it is concluded that there are significant departures from normality. 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. To test the hypothesis of independence, Ljung-Box statistics is estimated for the returns and squared returns, and also reported in Table 1. From these test statistics, we certainly can reject the null of white noise and assert that these return series are autocorrelated.

Table 1
Descriptive Statistics for ISE 100 Stock Returns

	ISE100
No. of observation	4914
Mean	0.002
Standard deviation	0.029
Skewness	-0.061
Kurtosis	6.176
Minimum	-0.199
Maximum	0.178
J-B	2067.95*
$Q(10)$	91.78*
$Q(20)$	100.12*
$Q(40)$	119.49*
$Q_S(10)$	1273.20*
$Q_S(20)$	1662.60*
$Q_S(40)$	2091.70*

Notes: J-B denotes Jarque-Bera (1980) normality test statistic. * denotes significance at 1% level. $Q(.)$ and $Q_s(.)$ are the Ljung-Box statistic for returns and squared returns up to 10, 20, and 40 lags, respectively.

Empirical Results

Before analyzing the long memory in returns and volatility, we test whether or not the return series is a stationary process using the ADF, PP, and KPSS unit root tests. These tests differ in the null hypothesis. The null hypothesis of the ADF and PP tests is that a time series contains a unit root, while the KPSS test has the null hypothesis of stationarity. The results of these tests are reported in Table 2. The results of the ADF and PP unit root tests support the rejection of the null hypothesis of a unit root at the conventional significance levels. The KPSS test statistics also indicate that the return series is insignificant to reject the null hypothesis of stationarity. Hence, the return series is stationary, I(*0*) and suitable for the long memory tests.

Table 2
Unit root tests results.

	Trend	ISE100
ADF	η_μ	-19.687(9)*
	η_τ	-19.699(9)*
PP	η_μ	-63.363(17)*
	η_τ	-63.358(17)*
KPSS	η_μ	0.141(20)
	η_τ	0.049(20)

Note: η_τ and η_μ refer to the test statistics with and without trend, respectively. * denotes significance at 1% level.

Long Memory in Returns

The estimation results and diagnostic statistics of the ARFIMA(p, ξ, q) models are reported in Table 3. Following Cheung (1993), we estimate different specifications of the ARMA(p, ξ, q) with $p + q \leq 2$ for each return series. A conventional model selection criterion, the Akaike's Information Criterion (AIC), is used to choose the best model that describes the data. The preferred models for the return series is the ARFIMA(2, ξ ,2). The results indicate that the long memory parameter (ξ) is significantly different from zero. Hence, the ARFIMA model supports the significant evidence of long memory in the ISE-100 returns. The long memory in returns implies that stock prices follow a predictable behavior, which is inconsistent with the efficient market hypothesis. This result supports the findings of recent studies, which claim that long memory property is generally a characteristic of emerging rather than developed stock markets[6].

Table 3 also reports diagnostic statistics, which suggest that the standardized residuals display large excess kurtosis and skewness, suggesting significant departure from normality. The large value of the Jarque-Bera (*JB*) statistic also shows the residuals appear to be leptokurtic. Moreover, the test results also indicate the existence of significant ARCH effects in the standardized residuals. Hence, the diagnostic statistics imply that modeling only the return series is not appropriate to capture the presence of long memory in the Turkish stock market. We should also examine the long memory property of volatility.

[6] See for example Barkoulas *et al*.(2000), Sourial (2002), Limam (2003), Assaf (2006), Kang and Yoon, (2007), Floros *et a*l. (2007).

Table 3 Estimation Results of ARFIMA Models

	$(0,\xi,0)$	$(0,\xi,1)$	$(0,\xi,2)$	$(1,\xi,0)$	$(1,\xi,1)$	$(1,\xi,2)$	$(2,\xi,0)$	$(2,\xi,1)$	$(2,\xi,2)$
μ	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*	0.0018*
	(0.0008)	(0.0005)	(0.0005)	(0.0005281)	(0.0005)	(0.0006)	(0.0006)	(0.0007)	(0.0006)
ψ_1	-	-	-	0.0883*	0.00477	0.0928	0.0793*	0.6216*	-0.9748*
				(0.0240)	(0.1555)	(0.4469)	(0.0268)	(0.1727)	(0.0780)
ψ_2	-	-	-	-	-	-	-0.0130	-0.0579*	-0.7523*
							(0.0174)	(0.0144)	(0.0813)
ξ	0.0744*	0.0234	0.0227	0.0187	0.0231	0.0263	0.0285	0.0650	**0.0480***
	(0.0117)	(0.0165)	(0.0225)	(0.0187)	(0.0197)	(0.0297)	(0.0228)	(0.0416)	(0.0135)
θ_1	-	0.0841*	0.0849*	-	0.0797	-0.0119	-	-0.5788*	1.0284*
		(0.0211)	(0.0272)		(0.1452)	(0.4667)		(0.1905)	(0.0709)
θ_2	-	-	0.0008	-	-	-0.0110	-	-	0.7940*
			(0.0191)			(0.0582)			(0.0736)
$\ln(L)$	10415.6609	10422.9116	10422.9126	10422.7606	10422.9121	10422.9272	10423.0418	10423.8765	10430.394
AIC	-4.23796	-4.24050	-4.24009	-4.24044	-4.24009	-4.23969	-4.24015	-4.24008	**-4.24233**
Skewness	-0.0373	-0.0527	-0.0528	-0.0523	-0.0527	-0.0527	-0.0531	-0.0560	-0.0444
Excess Kurtosis	3.2566	3.2456	3.2444	3.2353	3.2450	3.2501	3.2528	3.2468	3.0936
J-B	1075.2*	1068.1*	1067.5*	1063.1*	1067.8*	1070.4*	1071.7*	1068.3*	994.66*
$Q(20)$	50.413*	36.867*	36.895*	37.392*	36.880*	36.723*	36.435*	33.522*	23.028**
ARCH(4)	154.70*	156.60*	156.56*	156.50*	156.56*	156.54*	156.61*	156.74*	154.72*

Notes: QMLE standard errors are reported in the parentheses below corresponding parameter estimates. $\ln(L)$ is the value of the maximized Gaussian Likelihood, and AIC is the Akaike information criteria. The Q(20) is the Ljung-Box test statistics with 20 degrees of freedom based on the standardized residuals. The ARCH(4) denotes the ARCH test statistic with lag 4. The skewness and kurtosis are also based on standardized residuals.
* and ** indicate significance levels at the 5% and 10%, respectively.

Long Memory in Volatility

The results of estimated the GARCH, IGARCH and FIGARCH models are reported in Table 4. The model with different orders is estimated. The model selection is based on the AIC and Ljung-Box Q-statistics. The model which has the lowest AIC and passes Q-test simultaneously is used. The best fitting specifications are reported in Table 4. As seen in the Table 4, the sum of the estimates of α_1 and β_1 in the GARCH model is very close to one, indicating that the volatility process is highly persistent. For the FIGARCH model, the estimate of long memory parameter, *d*, is found to be significantly different from zero and is within the theoretical value, indicating that the volatility exhibits a long memory process in the Turkish stock market. This result shows the importance of modeling long memory in volatility and suggests that future volatility depends on its past realizations and therefore, is predictable. This result also supports the findings of other studies on both emerging and developed markets. In comparing a GARCH and an IGARCH models against the FIGARCH alternative, as can be seen in the table, in terms of diagnostic statistics, the FIGARCH model performs better than the other two models. For example, according to both the AIC and SIC criteria, the FIGARCH model fits the return series better than the GARCH and IGARCH models.

Table 4 also presents some diagnostics statistics. The standardized residuals exhibit skewness and excess kurtosis. This result suggests that we should use skewed Student-t distribution in the next analysis. The Pearson goodness-of-fit test statistic, P(60), indicates that the assumption of Gaussian distribution is inappropriate for capturing the dynamics of the ISE-100 returns. In addition, The BDS test statistic also statistically significant, implying that the residuals are far away from the independence. Hence, the dual long memory test should be carried out simultaneously in returns and volatility.

Table 4
Estimation results of FIGARCH models

	GARCH (1,0,1)	IGARCH (1,1,1)	FIGARCH (1,d,1)
μ	0.0016*	0.0016*	0.0016*
	(0.0003)	(0.0003)	(0.0003)
ω	0.2172*	0.1496*	0.3512*
	(0.0439)	(0.0276)	(0.1018)
α_1	0.1407*	0.1510*	0.1820**
	(0.0141)	(0.0145)	(0.0978)
β_1	0.8413*	0.8492	0.3729*
	(0.015866)		(0.1106)
d	-	1	**0.3715***
			(0.0379)
$\ln(L)$	10939.953	10935.855	10978.983
AIC	-4.45094	-4.44968	-4.46642
SIC	-4.44565	-4.44571	-4.45980
Skewness	-0.2037*	-0.2049*	-0.1894*
Excess kurtosis	1.7357*	1.7629*	1.5668*
J-B	650.87*	670.70*	532.03*
ARCH(4)	2.7484*	2.6611*	1.0757
BDS(4)	10.9353*	11.0954*	3.8694
P(60)	141.3846*	163.6557*	106.3175*

Notes: ARCH(4), Standard errors are reported in the parentheses below corresponding parameter estimates. BDS(4) represents the BDS statistics with the embedding dimension m = 4. P(60) is the Pearson goodness-of-fit statistic for 60 cells.
* denotes the significance levels at the 5%.

Dual Long Memory

The long memory property in conditional mean and conditional variance has been investigated separately in the proceeding subsections. Long memory dynamics, however, are commonly observed in both the conditional mean and conditional variance. Estimates of the ARFIMA-FIGARCH model under both the normal and skewed Student-*t* distributions are reported in Table 5.[7] As seen in the tables, both long memory parameters ξ and d are significantly different from zero, indicating that the dual long memory property is prevalent in the return and

[7] We also test for the persistence of the conditional heteroscedasticity models using the likelihood ratio (LR) tests for the linear constraints $\xi = d = 0$ (the ARMA-GARCH model). The LR tests statistics reject the ARMA-GARCH null hypotheses against the ARFIMA-FIGARCH model. Therefore, from the perspective of searching for a model that best describes the degree of persistence in both the mean and the variance of the stock return series, the ARFIMA-FIGARCH model appears to be the most satisfactory representation. The results are available from the authors upon request.

volatility of the Turkish stock market. Results also indicate that the skewed Student-*t* distribution performs better than the normal distribution since the parameter v statistically significant at 1% level. The lower values of P(60) test statistics also reconfirm the relevance of skewed Student-*t* distribution for all returns. Overall, significant long memory is reported for both the conditional mean and conditional variance. The long memory in the mean implies that stock prices follow a predictable behavior that is inconsistent with the efficient market hypothesis. 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.

Table 5
Estimation results of ARFIMA-FIGARCH models

	Normal	Skewed Student-*t*
μ	0.0016*	0.0019*
	(0.0005)	(0.0005)
ψ_1	-0.3917	-0.1374
	(0.3418)	(0.3519)
ψ_2	-0.4184	-0.3309
	(0.2590)	(0.2058)
ξ	**0.0508***	**0.0608***
	(0.0191)	**(0.0208)**
θ_1	0.4529	0.1796
	(0.3356)	(0.3638)
θ_2	0.4215	0.3034
	(0.2667)	(0.2085)
ω	0.4197*	0.4378*
	(0.1339)	(0.1519)
α_1	0.0811	0.0436
	(0.1321)	(0.1521)
β_1	0.2708**	0.2362
	(0.1499)	(0.1738)
d	**0.3602***	**0.3754***
	(0.0375)	**(0.0450)**
v	-	8.1566*
		(0.8158)
$\ln(\gamma)$	-	-0.0005
		(0.0212)
$\ln(L)$	11007.87	11090.74
AIC	-4.47614	-4.50905
ARCH(4)	1.0157	1.0420
RBD(4)	3.7051	2.8431
P(60)	107.5140*	48.7839

Notes: $\ln(\gamma)$ denotes asymmetry parameter. v is the tail parameter.* indicates significance level at 1% level.

5. Conclusions

In this paper, we have investigated the long memory properties of the returns and volatility of the Turkish stock market. The return series was modeled using an ARFIMA model. The results of the estimated ARFIMA model show the existence of long memory in return series. The GARCH, IGARCH, and FIGARCH models were used to model volatility. The results suggest that the FIGARCH model fits the data better than the other two models. The results of the FIGARCH model indicate that the estimate of the long memory parameter is statistically significant, suggesting that the volatility series is a long memory process. Since long memory dynamics are commonly observed in both the conditional mean and variance, particularly in the emerging markets, we also investigate the dual long memory property of the Turkish stock market. An ARFIMA-FIGARCH model was specified and estimated under both the normal and skewed Student-*t* distributions. The results suggest that the estimated ARFIMA-FIGARCH model provides the robustness of long memory test results, in contrast to the ARFIMA model or the FIGARCH model. The estimation results also indicate that the skewed Student-*t* distribution outperform the normal distribution. Long memory parameters both in the conditional mean and conditional variance were statistically significant, suggesting that the dual long memory property is prevalent in the returns and volatility.

In summary, the results show the evidence of long memory in the Turkish stock returns, which is inconsistent with the weak-form market efficiency, implying that the Turkish stock index (ISE-100) consists of the impact of news and shocks occurred in the recent past. Hence, speculative earnings could be gained via predicting stock prices. This study also presents evidence of long memory in volatility of the ISE-100. Since long memory model (FIGARCH) outperforms the traditional short-memory models (GARCH and IGARCH) risk analyzing methods requiring variance series, such as “value at risk”, give more efficient results when variance series of the ISE-100 is filtered by the long memory model, rather than short memory models. These findings would be helpful to the investors, financial managers, and regulators dealing with the Turkish stock market. The regulators should try to understand the sources of long memory in the market in order to improve efficiency.

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