VALUE-AT-RISK (VAR) ANALYSIS AND LONG MEMORY: EVIDENCE FROM FIAPARCH IN ISTANBUL STOCK EXCHANGE (ISE)

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Özet: Bu çalışmada İstanbul Menkul Kıymetler Borsası (IMKB) endeks getirileri, simetrik, asimetrik şartlı değişen varyans dahilinde uzun hafızaya sahip GARCH, IGARCH, GJR-GARCH, APARCH, FIGARCH ve FIAPARCH modelleriyle incelenmiştir. Kupiec-LR testi ile bir günlük Riske Maruz Değer'lerin (RMD) doğruluğu normal dağılım, student-t dağılımı ve skewed student-t dağılımı için incelenmiştir. ARCH modelleri menkul kıymetler borsasındaki kaldıraç etkisini ve şartlı oynaklık altındaki kısmi entegrasyonun varlığını kanıtlamaktadır. İMKB için FIAPARCH modeli, sözkonusu kaldıraç etkisi ve şartlı oynaklık altındaki kısmi entegrasyon için en iyi sonucu vermektedir. Ayrıca örneklem içi ve örneklem dışı RMD'ye dayanan Kupiec-LR testi, FIAPARCH modelinin uygunluğunu kanıtlamaktadır. Sonuç olarak student-t dağılımına sahip FIAPARCH modeli İMKB endeksine kaldıraç ve uzun hafıza özellikleri bakımından etkin RMD değerlerinin bulunmasına olanak vermektedir. Sözkonusu bulgular, finansal yöneticiler, yatırımcılar ve piyasa düzenleyiciler açısından İMKB'de yol gösterici niteliktedir.

Anahtar Kelimeler: Riske Maruz Değer, RMD, Uzun Hafıza, Kupiec-LR Testi, FIAPARCH Modeli

Abstract: In this study, I modeled Istanbul Stock Exchange (ISE) index returns using a number of symmetric and asymmetric conditional heteroscedasticity models including long memory models, namely GARCH, IGARCH, GJR-GARCH, APARCH, FIGARCH and FIAPARCH models. The accuracy of one-day-ahead Value-at-risk (VaR) is examined based on The Kupiec-LR test under the normal, student-t, and skewed student-t distributions. The results of ARCH class models show the existence of both leverage effect in stock exchange and fractional integration in conditional volatilities, which emphasizes the use of FIAPARCH model for ISE. Also the Kupiec LR test based on in-sample and out-of-sample VaR confirms the superiority of FIAPARCH model. Thus, Student-t FIAPARCH modeling the leverage and long memory properties in ISE index returns provides efficient VaR values. These findings would be helpful to the financial managers, investors, and regulators dealing with Istanbul Stock Exchange.

Key Words: Value-at-risk, VaR, Long memory, Kupiec-LR Test, FI-APARCH Model

I. Introduction

Measuring risk has long been a central concern in finance and remains a vital issue for many risk managers and investors. Especially value at risk (VaR) analysis became so popular to measure the risks of equities and banking since the value at risks analysis answers the questions such as what the financial loss will be in a specific time period with a given probability level of α, and proposes easiness to decision maker more than other risk measurement methods. VaR at a given probability level is the predicted maximum amount of

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loss for an asset (or portfolio) will not exceed VaR at a confidence level of $(1-\alpha)$ (Wu and Shieh, 2007: 248-259).

A vast finance literature has focused on risk measurement and shown that the predicted VaR is sensitive to the model used for filtering volatility series ((Tang and Shieh, 2006:437-448),(Wu and Shieh, 2007:248-259)). Thus, the model failing to capture the characteristics of financial data could have poor VaR prediction performance. Among others, Angelidis and Degiannakis (2005) examined the VaR performances of parametric, semi parametric and nonparametric methods for short and long positions in stock markets, commodity exchanges and currency markets. Their findings indicated that high accuracy of VaR forecasts in asset returns results from main characteristics of returns and that risk managers should prefer different volatility forecasting models for both positions especially at the high confidence levels. Also, Çifter and Özün (2007) evaluated the forecasting performance of ARCH class models for ISE index returns and found that volatility models should be selected based on treading positions and confidence interval. Hence I compute VaR for both long and short trading positions.

Although GARCH model adequately captures the volatility clustering, it fails to model the property of long-run dependencies between distance observations in volatility series, which is known as long memory in volatility. Thus, using GARCH model on stock return series having long memory in volatility could have poor VaR performance. Ballie *et al.* proposed the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model to capture the long memory behavior in volatility. Moreover, Tse (1998) proposed the fractionally integrated asymmetric power ARCH (FIAPARCH) model by generalizing the APARCH model to allow for modeling both long memory and asymmetry effect in volatility series. Degiannakis (2004) used ARCH class models on predicting VaR for daily and intra day returns, and found that FIAPARCH (1,d,1) model produces most accurate results to forecast volatility for asymmetric student-t distribution. Wu and Shieh (2007) predicted the VaR at short and long position for the bond returns that showed that FIGARCH (1,d,1) model provides more accurate in-sample and out-of-sample VaR than GARCH (1,1) models. Tu et al. (2008) investigated the performance of value at risk models on daily returns of Asian markets, and suggested that the APARCH models that are based on asymmetric student-t distribution were best models for Asian markets.

In this study, I investigate the properties of volatility in ISE National 100 index and calculate the VaR. For this aim before computing the VaR, I use a number of conditional heteroscedasticity models to capture the properties in conditional volatilities of ISE National 100 index. Also one day ahead in-sample and out-of-sample forecasting VaR performances are evaluated based on Kupiec LR test for both long and short trading positions.

The rest of the paper is organized as follows: the methodology is summarized in section 2. Section 3 gives information about dataset used and reports the empirical results. Section 4 is devoted to conclusions.

II. Methodology

In this section, after the conditional heteroscedasticity models of GARCH, IGARCH, GJR-GARCH, APARCH, FIGARCH and FI-APARCH are discussed then I present VaR method and Kupiec LR test used for measuring the accuracy of VaR forecasts.

A.Conditional Heteroscedasticity Models

It was empirically proven that the GARCH model captures the volatility clustering, which denotes the tendency of the high (low) returns to follow the high (low) returns (among others, see Niguez (2003), Huang and Lin(2004), So and Yu (2005), Ewing and Malik (2005), Chiu et al.(2006), Bali et al. (2006), So and Yu (2006)) The GARCH model proposed by Bollerslev (1986) by adding the lag value of conditional variance to the ARCH model generated by Engle(1982) can be expressed as below.

$$\varepsilon_t = \sigma_t z_t, \qquad z_t \overset{i.i.d}{\sim} f(0,1) \tag{1}$$

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2 \tag{2}$$

where $f(.)$ represents the distribution function with zero mean and a variance of 1. (L) is the lag operator and to ensure the stationarity of volatility series, *I(0)*, all the roots of $\alpha(L)$ and $[1-\alpha(L)-\beta(L)]$ are constrained to lie outside the unit circle.

In case of volatility persistency which is the sum of α and β in GARCH model equals to 1, volatility series have unit-root and thus, the variance is integrated of order 1, or *I(1)*. Engle and Bollerslev (1986) also developed the IGARCH (integrated GARCH) model that considers the unit root process in volatility. IGARCH model can be expressed as below.

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

where $\phi(L) \equiv [1-\alpha(L)-\beta(L)](1-L)^{-1}$ and $v_t = \varepsilon_t^2 - \sigma_t^2$.

In addition to volatility clustering and persistency, another characteristic of volatility is leverage effect or asymmetry effect, that is, negative return shocks causes more volatility than positive return shocks of the same magnitude. The GJR-GARCH (Glosten et al. 1993) and APARCH (Ding et al. 1993) were developed to model the asymmetry effect on volatility.

Glosten et al. (1993) proposed GJR- GARCH model by introducing asymmetry term to GARCH model and can be shown as below.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i \varepsilon_{t-i}^2 + \xi_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p}\beta_j \sigma_{t-j}^2 \tag{4}$$

Where S_t^- is the dummy variable that takes a value of 1 when the error term, ε_t^2, is negative and it takes 0 value when it is equal to zero or positive statistically significant and positive ξ coefficient in model denotes the existence of leverage effect in stock returns.

Another model capturing asymmetry effect in financial time series is the Asymmetric Power ARCH (APARCH) model proposed by Ding, Granger and Engle (1993) is expressed as follows:

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^{q}\alpha_i(|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^{p}\beta_j \sigma_{t-j}^\delta \tag{5}$$

where $\alpha_0 > 0,\ \delta \geq 0,\ \alpha_i \geq 0\ and\ -1 < \gamma_i < 1\ for\ i = 1,...,q\ \ and\ \ \beta_j \geq 0\ \ for\ \ j = 1,...,p.$ δ is the power parameter and γ_i denotes asymmetry parameter. Statistically significant and positive (negative) γ_i means that the past negative (positive) shocks have deeper effect than positive (negative) shocks on conditional variance. In addition to capture the asymmetry effect, APARCH model allows for utilizing the Box-Cox transformation for modeling distribution properties of data. Thus, in contrast to GARCH model assuming that the power parameter is 2 under normal distribution assumption, APARCH model estimates the δ freely for including the distribution characteristics to model(For more information see also Longmore and Robinson(2004)).

The GARCH model proposed by Bollerslev (1986) assumes that the conditional variance is stationary, I(0), thus a shock in variance decays exponentially to zero. Conversely, the IGARCH model developed by Engle and Bolleslev (1986) assumes that the shock on volatility persists indefinitely since the variance series have unit root. However, it is proven that the effects of shocks on volatility series decay hyperbolically and continues over long time, which is named as “fractional integration” or “long memory” property (Among others Li(2002), Vilasuso (2002), pong et al (2004), Martens and Zein (2004), Kilic (2004), Vougas (2004), Bhardwaj and Norman (2006), Flores et al (2007), Kang and Yoon (2007)). Thus, autocorrelation coefficients of squared daily stock returns decay very slowly. To model for long memory in volatility, Ballie, et al (1996) developed Fractionally Integrated GARCH (FIGARCH) model by modifying the first differencing operator $(1-L)$ in Eq. (3) to fractional differencing operator $(1-L)^d$ FIGARCH (1,d,1) model is defined as follows:

$$\phi(L)(1-L)^d \varepsilon_t^2 = \omega + [1-\beta(L)]v_t \quad (6)$$

where, d is the memory parameter. Statistically significant memory parameter taking a value between 0 and 1 (0<d<1) means that the conditional variances series have long memory property,

Tse (1998) proposed Fractionally Integrated APARCH (FIAPARCH) model by generalizing the APARCH model to allow for persistence in the conditional variance. FIAPARCH model can be shown as below:

$$\sigma_t^\delta = \omega + \{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\}(|\varepsilon_t| - \gamma\varepsilon_t)^\delta \quad (7)$$

Similar to FIGARCH model, d is the memory parameter and when 0<d<1it is said that conditional variance series have long memory property. Hence, impact of a shock on the conditional variance decays at a hyperbolic rate.

B. Value at Risk (VaR)

VaR is the measure of maximum loss that the investors will experience during severe adverse market fluctuations. In addition to long positions, short trading positions are affected by adverse price movements, hence the VaR of α quantile for long and short trading positions are estimated as below:

Under the normal distribution assumption;

$$VaR_{long} = \hat{\mu}_t - z_\alpha \hat{\sigma}_t \quad (8)$$

$$VaR_{short} = \hat{\mu}_t + z_\alpha \hat{\sigma}_t \quad (9)$$

Under student-t distribution assumption;

$$VaR_{long} = \hat{\mu}_t - st_{\alpha,v} \hat{\sigma}_t \quad (10)$$

$$VaR_{short} = \hat{\mu}_t + st_{\alpha,v} \hat{\sigma}_t \quad (11)$$

Here $\hat{\mu}_t$ and $\hat{\sigma}_t$ denotes conditional mean and variance forecasted at time *t-1*. z_α and $st_{\alpha,v}$ are right and left quantile values at $\alpha\%$ for normal distribution and student-t distribution, respectively.

C. Kupiec LR test

Kupiec LR test developed by Kupiec (1995) was used to evaluate the performance of computed VaR at pre-specified level ranging from 5% to 0.25%.

Kupiec LR (1995) test relies on the failure rate which is the rate of the returns that exceeds the VaR value to the total observation. When the failure close to the pre-determined VaR level α indicates that VaR was computed efficiently. Kupiec LR (1995) is defines as follows:

$$LR = -2\ln\left[(1-\alpha)^{N-x}(\alpha)^x\right] + 2\ln\left[(1-\hat{f})^{N-x}(\hat{f})^x\right] \sim \chi_1^2 \quad (12)$$

$\hat{f} = \frac{x}{N}$ where $\hat{f}$ is the failure rate, *x* is the number of observations exceeding (in absolute value) the forecasted VaR and *N* is the sample size. Under the null hypothesis that the failure rate equals the pre-specified VaR level α LR test statistics is asymptotically distributed as $\chi^2_{(1)}$.

III. Data And Empırıcal Results

A. Data

The data consists of daily closing price of ISE-National 100 index for the period covering from 02 January 2002- 17 April 2009. The sample data were obtained from Istanbul Stock Exchange. The daily stock returns are defined as the logarithmic difference of the daily closing index prices.

Table 1 reports the descriptive statistics for daily returns. The return series are negatively skewed and leptokurtic. In addition Jarque – Bera (JB) statistics reveal that return series departures from normality. The Ljung-Box Q statistics for the returns and squared returns indicate that both the return and squared return series are autocorrelated, suggesting the existence of volatility clustering of an ARCH process in the series (Since the high order autocorrelation in returns might be the result of the long memory in returns; the ARFIMA (p,q,d) model is used for modeling long memory in return series. However, insignificant long memory parameter indicates that there exists short memory in returns).

Table 1: *Descriptive Statistics for ISE-100 Index Returns*

	ISE-100
Mean	0.000
Standard Deviation	0.022
Skewness	-0.006
Kurtosis	6.474
Minimum	-0.133
Maximum	0.121
J-B	890.5*
No. of observations	1772
$Q(10)$	25.067*
$Q(20)$	34.589*
$Q(40)$	65.169*
$Q_S(10)$	198.77*
$Q_S(20)$	318.49*
$Q_S(40)$	383.48*

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

Table 2 summarizes the Dickey Fuller (ADF) and Phillips-Perron (PP) unit root test results. According to both two unit root tests the return serial is stationary and appropriate for empirical analysis.

Table 2: *Unit Root Tests Results*

		ISE100 returns
ADF	η_μ	-7.681*(11)
	η_τ	-7.713*(11)
PP	η_μ	-40.827*(19)
	η_τ	-40.790*(19)

Notes: η_τ and η_μ refer to the test statistics with and without trend, respectively. The numbers in parenthesis are optimum lag number. * denotes the significance level at 1%.

B.Empirical Results

B1. Estimation Results

Table 3 represents the estimation results of GARCH(1,1), IGARCH(1,1), GJR-GARCH(1,1), APARCH(1,1), FIGARCH(1,d,1) and FIAPARCH(1,d,1) models under normal, Student-t, and skewed Student-t distribution assumptions(The model selection is based on Akaike's information criterion (AIC) and Ljung-Box Q statistics. The model which has the lowest AIC and passes Q-test simultaneously is selected). The estimated GARCH parameters α_1 and β_1 are positive and statistically significant.

In addition the sum of α_1 and β_1 are very close to 1, suggesting that the volatility process is highly persistent. The statistically significant asymmetry parameters of both GJR-GARCH and APARCH models indicate the existence of leverage effect in Istanbul Stock Exchange. Hence, negative shocks have deeper impact on conditional volatility than positive shocks of the same magnitude. Long memory or fractional integration parameters of both FIGARCH and FIAPARCH models are statistically significant and lie between 0.35 and 0.45. Hence, volatility of index returns exhibits long memory property. Thus, the effect of a shock on conditional volatility decays hyperbolically, that is volatility of returns can be characterized by mean-reverting fractionally integrated process. Long memory property of stock index volatility is of great importance since it indicates that future volatility is predictable due to dependence of future volatility to its past realizations. For all models estimated, the tail parameters v are statistically significant, suggesting that returns series have fat tails. However, asymmetry parameters are insignificant. Hence, distributions of the return series do not fit the skewed Student-t distribution. The ARCH LM test statistics for residuals supports that there is no ARCH effect in the residuals. In conclusion, the FIAPARCH model with normal and Student-t distributions can capture the main properties of volatility clustering, long memory, asymmetry, and fat tails in ISE National 100 index returns.

Table 3: *Estimation Results Of Volatility Models For Ise100 İndex Returns*

	GARCH			IGARCH			GJR-GARCH			APARCH			FIGARCH			FIAPARCH		
	N	T	SKT	N	T	SKT	N	T	SKT	N	T	SKT	N	T	SKT	N	T	SKT
μ	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001 (0.000)	0.001*** (0.000)	0.001 (0.000)	0.001 (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001 (0.000)	0.001*** (0.000)	0.001*** (0.000)
ω	0.120* (0.028)	0.149* (0.047)	0.150* (0.047)	0.063* (0.014)	0.086** (0.026)	0.076* (0.026)	0.143* (0.031)	0.180* (0.051)	0.181* (0.052)	0.036 (0.034)	0.180 (0.229)	0.168 (0.216)	0.189* (0.060)	0.252** (0.119)	0.252** (0.121)	0.216 (0.194)	1.706 (2.087)	1.647 (1.977)
α_1	0.097* (0.010)	0.094* (0.017)	0.094* (0.017)	0.110* (0.009)	0.115** (0.018)	0.115* (0.018)	0.067* (0.009)	0.058* (0.017)	0.058* (0.017)	0.069* (0.012)	0.092* (0.018)	0.091* (0.018)	0.175* (0.050)	0.159 (0.101)	0.160 (0.102)	0.153*** (0.067)	0.179*** (0.100)	0.178*** (0.102)
β_1	0.881* (0.011)	0.875* (0.022)	0.875* (0.021)	0.890	0.885	0.885	0.873* (0.011)	0.865* (0.022)	0.865* (0.022)	0.864* (0.014)	0.855* (0.023)	0.854* (0.023)	0.526* (0.076)	0.461* (0.137)	0.457* (0.139)	0.460* (0.111)	0.465* (0.153)	0.461* (0.154)
d	-	-	-	-	-	-	-	-	-	-	-	-	0.450* (0.063)	0.405* (0.086)	0.401* (0.085)	0.394* (0.100)	0.390* (0.100)	0.387* (0.099)
ξ	-	-	-	-	-	-	0.064* (0.017)	0.076* (0.027)	0.076* (0.027)	-	-	-	-	-	-	-	-	-
γ	-	-	-	-	-	-	-	-	-	0.155*** (0.089)	0.212* (0.073)	0.210* (0.073)	-	-	-	0.183* (0.045)	0.261* (0.085)	0.260* (0.086)
δ	-	-	-	-	-	-	-	-	-	2.369* (0.253)	2.000* (0.324)	2.026* (0.332)	-	-	-	1.572* (0.130)	1.623* (0.240)	1.632* (0.240)
v	-	8.131* (1.220)	8.170* (1.290)	-	7.130** (1.140)	7.156* (1.160)	-	8.242* (1.266)	8.262* (1.267)	-	8.246* (1.292)	8.272* (1.306)	-	8.028* (1.343)	8.063* (1.367)	-	8.190* (1.352)	8.215* (1.364)
$\ln(\lambda)$	-	-	-0.021 (0.034)	-	-	-0.014 (0.036)	-	-	-0.020 (0.034)	-	-	-0.020 (0.034)	-	-	-0.021 (0.034)	-	-	-0.019 (0.034)
$\ln(L)$	4376	4409	4409	4373	4405	4405	4381	4414	4414	4382	4413	4413	4379	4408	4408	4385	4416	4416
AIC	-4.938	-4.974	-4.973	-4.935	-4.970	-4.969	-4.942	-4.977	-4.976	-4.942	-4.976	-4.975	-4.939	-4.971	-4.970	-4.944	-4.976	-4.975
ARCH(5)	0.109	0.116	0.114	0.122	0.121	0.119	0.082	0.132	0.130	0.080	0.141	0.136	0.179	0.200	0.197	0.065	0.116	0.114

Notes: QMLE standard errors are reported in parentheses below corresponding parameter estimates. *, **, and *** denote the significance level at 1%, 5% and 10%, respectively. *d* is the long memory parameter. N, T and SKT, represents normal, Student-t and skewed Student-t distributions, respectively. ξ denotes the asymmetry parameter for GJR-GARCH model. For APARCH and FIAPARCH models, γ and δ are asymmetry and power parameters respectively. ln(γ) denotes asymmetry parameter. *v* is tail parameter. $\ln(L)$ Represents log likelihood value. ARCH denotes ARCH LM test. AIC is the value of Akaike information criteria.

B2. In sample VaR results

Based on estimation results, FIAPARCH was chosen as the best model for ISE 100 index returns because of the long memory and leverage effects in stock market. Heree, in sample VaR values were computed to examine the estimated model's goodness-of-fit ability.

Table 4: *In-Sample VaR Computed by FIAPARCH for ISE-100 Index Returns*

Short position				Long position			
α Quantile	Failure rate	Kupiec	P-value	α Quantile	Failure rate	Kupiec	P-value
Gauss distribution							
0.9500	0.958	2.659	0.103	0.050	0.046	0.697	0.404
0.9750	0.976	0.122	0.727	0.025	0.027	0.313	0.576
0.9900	0.989	0.093	0.761	0.010	0.014	2.688	0.101
0.9950	0.992	2.551	0.110	0.005	0.011	8.780	0.003*
Student-t distribution							
0.9500	0.955	1.123	0.289	0.050	0.051	0.025	0.875
0.9750	0.977	0.437	0.508	0.025	0.025	0.002	0.967
0.9900	0.992	0.442	0.506	0.010	0.012	0.583	0.445
0.9950	0.997	1.044	0.307	0.005	0.005	0.002	0.961

Note: *, and ** denote the significance level at 1%, 5%, respectively

Table 4 reports the failure rates and their corresponding Kupiec LR tests. The null hypothesis that failure rate is equal to the pre-specified VaR level indicates that the VaR model is estimated accurately since the model explain the actual observations very well. The null hypothesis that the failure rate equals to prescribed quantiles in the normal FIAPARCH for long position is rejected only for α value of 0.005. However, Student-t FIAPARCH model performs better than that with normal distribution. For long and short positions the null hypothesis of $f = \alpha$ can not be rejected, in all quantile, thus, student-t FIAPARCH model increased the VaR forecasting efficiency.

B3. Out-of-sample VaR results

Out-of-sample VaR values were computed to evaluate the forecasting quality of the FIAPARCH model, that is crucial for investors using forecasted values to eliminate the uncertainty on maximum loss investors will incur. Also, model is estimated with normal and Student-t distributions since in-sample and out-of-sample forecasting performance could be different based on distribution assumptions(See Wuu and Shieh (2007) for details). Table 5 reports out-of-sample VaR values. Consistent with in-sample VaR results, failure rate significantly exceeds only the prescribed quantile of 0.005 with normal distribution for long position. Also all the Student-t models do not reject the null hypothesis of $f = \alpha$. Hence, Student-t distribution performs better than normal distribution in great extend. High goodness of fit ability and forecasting quality confirms that FIAPACH model can model the characteristics of Istanbul Stock Exchange adequately.

Table 5: *Out-of-Sample VaR Computed by FIAPARCH for ISE-100 Index Returns*

Short position				Long position			
α Quantile	Failure rate	Kupiec	P-value	α Quantile	Failure rate	Kupiec	P-value
Gauss distribution							
0.9500	0.949	0.009	0.925	0.050	0.054	0.217	0.641
0.9750	0.971	0.336	0.562	0.025	0.031	0.687	0.407
0.9900	0.985	1.417	0.234	0.010	0.015	1.417	0.234
0.9950	0.992	1.184	0.277	0.005	0.012	4.026	0.045**
Student-t distribution							
0.9500	0.947	0.079	0.779	0.050	0.061	1.413	0.235
0.9750	0.975	0.004	0.948	0.025	0.032	1.153	0.283
0.9900	0.990	0.002	0.967	0.010	0.014	0.679	0.410
0.9950	0.997	0.347	0.556	0.005	0.005	0.001	0.977

Note: *, and ** denote the significance level at 1%, 5%, respectively

IV. Conclusion

This paper has investigated the volatility properties of Istanbul Stock Exchange. For modeling the volatility, the GARCH, IGARCH, GJR-GARCH, APARCH, FIGARCH, and FIAPARCH models with normal, Student-t, and skewed Student-t distributions have been used. The asymmetric short memory models of GJR-GARCH and APARCH models indicate that there exists leverage effect in stock market. Moreover, significant long memory parameter in FIGARCH model suggests that conditional volatility exhibits long memory property. Thus, these evidence lead authors to use the FIAPARCH model capturing the asymmetry and long memory properties jointly in conditional volatility series. Significant long memory and asymmetry parameters confirm that asymmetry and fractional integration are the characteristics of Istanbul Stock Exchange. For all models, symmetric distributions perform better than asymmetric distribution since the asymmetric distribution parameters ln(λ) are statistically insignificant. Comparing the estimated in-sample and out-of-sample VaR values based on Kupiec LR test, the Student-t model performs better than the normal distribution in describing the return series in Istanbul Stock exchange.

Since the performance of VaR calculations depend on the forecasts of mean and variance filtered by volatility model, the selection of the model is crucial for accuracy of forecasting. Thus, Student-t FIAPARCH modeling the leverage and long memory properties in ISE index returns provides efficient VaR values. Also, to the best of authors' knowledge, no such study has been done on the Turkish Stock Market by using asymmetric long memory models.

Thus, findings of this paper would be helpful to the financial managers, investors, and regulators dealing with Istanbul Stock Exchange.

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