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Forecasting World Stock Markets Volatility

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Abstract

Volatility forecasting is important for option pricing, risk management and portfolio management. In the literature the best forecast volatility model is controversial. Some study support the power of historical GARCH models, while some support asymmetric GARCH models. The purpose of study is to employ seven different GARCH class models to forecast in-sample of daily stock market volatility in 10 different countries. The findings of study emphasize that the class of asymmetric volatility models perform better in forecasting of stock market volatility than the historical model.

Keywords: Volatility, world stock exchange market, GARCH class models, forecasting
JEL Classification Codes: E44; C32; C53; G15

1. Introduction

Financial market volatility has impact on financial regulation, monetary policy and macroeconomy. So the purpose of study is to employ seven different models to forecast in-sample of daily stock market volatility in 10 different countries to put the best volatility forecasting model.

In the literature many researchers focus on financial market volatility of different countries (French, Schwert ve Stambaugh, 1987; Schwert, W. 1989; Bollerslev, Litvinova ve Tauchen, 2006; Appiah-Kusi ve Menyah, 2003; Kayahan, Stengos ve Saltoğlu, 2002; Bollerslev ve Zhou, 2006), but the best forecast volatility model is controversial. Some empirical studies have emphasized the power of historical GARCH models (Mcmillian Speigh and Gwilym, 2000). For instance, Braisford and Faff (1996) stress the ARCH class of models provide superior forecasts of volatility. Additionally Ederington and Guan (2000) compare the forecasting ability of some volatility models and conclude that GARCH(1,1) generally yields better forecasts than the historical standard deviation and exponentially weighted moving average models. In the contrast, some empirical studies have emphasize the power of asymmetries on the forecast performance of GARCH models (Maris and et all.,2004 ; Loudan, Watt and Yadav, 2000). For example, Awartani and Corradi (2005) investigate the out of sample predictive ability of different GARCH models and conclude the GARCH(1,1) is beaten by the asymmetric GARCH models. Addition to that Franses and Dijk (1996) study the performance of the GARCH model and two of its non-linear modifications to forecast weekly stock market volatility. They conclude that the asymmetric model (QGARCH) is the best when the estimation sample does not contain extreme observations.

To put the best volatility forecasting model, this paper is organized as follows: Section 1, introduction of studies. Section 2, describes the research method employed to collect. Section 3 describes data. Section 4 shows the empirical evidence of GARCH class models. Section 5 provides the summary and conclusion.

2. Methodology

First of all the stationarity of the time series is tested by the "Augmented Dickey-Fuller (ADF)" unit root test (Dickey and Fuller, 1981). Secondly, for modeling conditional mean, we detected the fitted AR, MA and ARIMA models using autocorrelation and partial autocorrelation function. In this context, if a time series can be expressed as a function of its lagged values, it can be defined as an autoregressive process (AR) and if the value of a variable at time t is determined by the lagged value of the residual in the same period and the previous, this process is defined as a moving average (MA) process. Also, it is more appropriate to model time series as a combination of autoregressive and moving average components. These processes are called ARMA processes (Enders, 2004).

Thirdly, after determining the conditional mean, we test for autoregressive conditional heteroscedasticity (ARCH) in the residuals using Lagrange multiplier (LM) (Engle 1982). Fourthly having confirmed the persistence of conditional heteroscedasticity, we now focus on the volatility modeling using ARCH class models (Tsay, 2005):

The most popular class of models for conditional volatility is the AutoRegressive Conditional Heterocedasticity (ARCH) model introduced by Engle (1982).

GARCH Model:

The GARCH models, which are generalized ARCH models, allow for both autoregressive and moving average components in the heteroscedastic variance developed by Bollerslev (1986) and stated as follows:

$$r_t = \sqrt{h_t}\,\varepsilon_t \tag{1}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i r^2{}_{t-i} + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{2}$$

$p \geq 0$, q>0, α_0 >0, $\alpha_i \geq 0 \;\forall\, i \geq 1$, i =1,……..p, $\beta_j \geq 0 \;\forall\, j \geq 1$

PARCH Model:

Taylor (1986) and Schwert (1989) introduced the standard deviation GARCH model, where the standard deviation is modeled rather than the variance. This model, along with several other models, is generalized in Ding et al. (1993) with the Power ARCH specification. In the Power ARCH model, the power parameter δ of the standard deviation can be estimated rather than imposed, and the optional γ_i parameters are added to capture asymmetry of up to order r and stated as formula 3:

$$\sigma_t^{\delta} = \varpi + \sum\nolimits_{i=1}^{q} \beta_j \sigma_{t-j}^{\delta} + \sum\nolimits_{i=1}^{p} \alpha_i (|e_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} \tag{3}$$

$\delta > 0$, $|\gamma_i| \leq 1$, all i =1,2,…r, γ_i =0, all i > r and r $\leq$ p

TARCH Model:

Threshold GARCH model was introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993). The generalized specification for the conditional variance is given by Formula 4:

$$\sigma_t^{\delta} = \varpi + \sum\nolimits_{j=1}^{q} \beta_j \alpha_{t-j}^2 + \sum\nolimits_{i=1}^{p} \alpha_i \varepsilon_{t-i}{}^2 + \sum\nolimits_{k=1}^{r} \gamma_k \varepsilon^2{}_{t-k} \bar{I}_{t-k} \tag{4}$$

where $\bar{I}_t = 1$ if $\varepsilon_t \prec 0$, and 0 otherwise

C-GARCH Model:

The conditional variance in the GARCH (1, 1) model:

$$\sigma_t^2 = \overline{\varpi} + \alpha({\mu^2}_{t-1} - \overline{\varpi}) + \beta({\sigma^2}_{t-1} - \overline{\varpi}) \tag{5}$$

which shows mean reversion to $\overline{\varpi}$, which is a constant for all time. By contrast, the component model allows mean reversion to a varying level, m_t modeled as:

$$\sigma_t^2 = m_t + \alpha({\varepsilon^2}_{t-1} - m_{t-1}) + \beta({\sigma^2}_{t-1} - m_{t-1}) \tag{6}$$

$$m_t = \varpi + p(m_{t-1} - \varpi) + \Phi(\varepsilon_{t-1} - {\sigma^2}_{t-1}) \tag{7}$$

IGARCH Model:

Integrated Generalized Autoregressive Conditional Heteroscedasticity is a restricted version of the GARCH model (Engle 1982 and Bollerslev, 1986). In this model the sum of the persistent parameters sum up to one, and therefore there is a unit root in the GARCH process and stated as Formula 8:

$$\sigma_t^2 = \alpha_i {e_{t-i}}^2 + \beta_j \sigma_{t-j}^2 \tag{8}$$

$$\beta_j = 1 - \alpha_i$$

E-GARCH Model:

The EGARCH or Exponential GARCH model was proposed by Nelson (1991). The specification for the conditional variance is:

$$\log(\sigma_t^2) = \varpi + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{e_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \tag{9}$$

The presence of leverage effects can be tested by the hypothesis that $\gamma_i \prec 0$. The impact is asymmetric if $\gamma_i \neq 0$.

GARCH-M Model:

GARCH-M model which depend on Engle (1982) and Bollerslev (1986), stated as follows:

$$R_t = \beta R_{t-i} + \gamma {h_t}^2 + \mu_t \tag{10}$$

$$h_t^2 = V(\mu_t / \Omega_{t-1}) = E({\mu_t}^2 / \Omega_{t-1}) = \alpha_0 + \sum_{i=1}^{q} \alpha_1 \mu_{t-i} + \sum_{i=1}^{p} \Phi_i h_{t-i} \tag{11}$$

İf Ω_{t-1} is information set of R_t and h_t;

$$\Omega_{t-1} = (h_{t-1}, h_{t-2}, \ldots\ldots\ldots\ldots, R_{t-1}, R_{t-2} \ldots\ldots)$$

Bollerslev (1986)'s positivist condition is not necessary for IGARCH model ($\alpha_t \geq 0$, i=1,2,…q and $\Phi_t \geq 0$, i=1,2,…p).

3. Data

The study covers 11 daily stock exchange market indexes as stated Table 1. The data required for analyzing were obtained from yahoo-finance and Central Bank of the Republic of Turkey for the period 01.01.1995–31.02.2007. Eviews 5.1 software package was used for the analysis.

We use the return of all variables by the calculating algebraic equation

$R = (F_{t+1} - F_t)/F_t$,

where F_t = close price of the t_{th} period, F_{t+1} = close price of the $t+1_{th}$ period

Table 1: World stock exchange markets

Index	Countries	
FTSE–100	England	Europe
AEX	Netherlands	Europe
ATX	Austria	Europe
DAX	German	Europe
DJ	USA	USA
IPC	Mexico	USA
NASDAQ	USA	USA
SMI	Switzerland	Europe
CAC–40	France	Europe
NIKEI–225	Japan	Asia-Pacific
IMKB–100	Turkey	Europe

4. Empirical Findings

We use daily return of world indexes to analyze the period ranging from the 1th of January 1995 to the 31th of February 2007. Some descriptive statistics of world indexes returns are presented in Table-2.

Table 2: Summary statistics of world stock exchange market

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
FTSE–100	2.80E-05	6.90E-05	0.007291	-0.006694	0.001256	-0.147243	6.078522
AEX	1.31E-05	0.000131	0.017668	-0.106320	0.002976	-1.474.842	5.300.373
ATX	622E-05	0.000110	0.007390	-0.012070	0.001428	-0.774475	8.179.089
DAX	4.80E-05	0.000121	0.009230	-0.008014	0.001798	-0.146544	6.080.049
DJ	4.37E-05	5.34E-05	0.006877	-0.008329	0.001156	-0.246930	7.627.211
IBOVESPA	1.15E-05	0.000138	0.033807	-0.199702	0.004425	-3.044.254	1.383.579
IPC	9.18E-05	9.76E-05	0.015165	-0.016838	0.001946	0.025822	1.020.499
NASDAQ	5.61E-05	0.000178	0.017131	-0.012386	0.002219	0.032418	7.234.589
SMI	4.78E-05	8.95E-05	0.008736	-0.006724	0.001364	-0.098151	7.394.300
CAC–40	4.46E-05	7.42E-05	0.008925	-0.009156	0.001669	-0.080436	5.913.484
NIKEI–225	-2.78E-06	6.22E-07	0.007957	-0.007430	0.001482	-0.026173	4.981.314
IMKB–100	8.79E-05	8.66E-05	0.008707	-0.009702	0.001442	-0.056294	7.430.832

In this study, the conditional volatility of world markets should be estimated by a correctly specified GARCH class models. As the first step in the testing procedure, world stock exchange market returns were tested for possible unit root processes by Augmented Dickey Fuller (ADF) procedure. For all the series, the null hypotheses of unit root were rejected (Table 3).

Table 3: Unit root tests result

Variables	ADF- t statistic-for the model without trend	ADF- t statistic -For the model with trend
FTSE–100	-35,72069*	-35,72862**
AEX	-55,68900*	-55,68294**
ATX	-52,49693*	-52,55528**
DAX	-56,21506*	-56,21218**
DJ	-55,61533*	-5565015**
IPC	-50,10836*	-50,10262**
NASDAQ	-54,50971*	-54,52801**
SMI	-53,38830*	-53,37710**
CAC–40	-55,26438*	-55,26196**
NIKEI–225	-57,52543*	-57,54019**
IMKB–100	-53,58736*	-53,63203**

* MacKinnon critical values for the significance level of 1 %, 5 % and 10 % respectively are as follows: - for the model without trend -3,43, -2,86 and -2,56, for the model with trend ; -3,96, -3,41 and -3,12.

Especially for some return series for some GARCH class models, outliers potentially tend to create problems in the identification and estimation of GARCH type models. For this, outlier dummies used for the detection of spurious ARCH effect. Because Van Dijk *et al.* (1999) showed that neglected additive outliers in return series are negatively effect on the ARCH models (Charles and Darne, 2005).

For modeling the conditional mean which is the first step of modeling conditional volatility of stationary worlds stock return series, we decided to analyze which of the AR, MA and ARIMA models best describe the conditional mean. The parameters estimated are presented in Table-4.

Table 4: ARMA models parametric estimates

	Variable	Coefficient	Std. Error	t-Statistic	Prob.
FTSE–100	*MA(3)*	-0.094401	0.017988	-5.248039	0.0000
	AR(1)	-0.701580	0.132089	-5.311.424	0.0000
	AR(2)	0.051100	0.019846	2.574.859	0.0101
	MA(1)	0.708905	0.131501	5.390.885	0.0000
ATX	*MA(1)*	0.045467	0.018227	2.494413	0.0127
DAX	*AR(1)*	0.733693	0.320708	2.287729	0.0222
	MA(1)	-0.750595	0.311884	-2.406651	0.0162
DJ	*AR(1)*	0.827298	0.189684	4.361451	0.0000
	MA(1)	-0.842875	0.181713	-4.638499	0.0000
IPC	*AR(1)*	0.098562	0.018025	5.468183	0.0000
NASDAQ	*AR(1)*	-0.784689	0.009700	-80.89607	0.0000
	AR(2)	-0.982264	0.010343	-94.97311	0.0000
	MA(1)	0.790494	0.012080	65.43936	0.0000
	MA(2)	0.971455	0.013065	74.35407	0.0000
SMI	*AR(1)*	-1.603963	0.083273	-19.26152	0.0000
	AR(2)	-0.765396	0.078062	-9.804979	0.0000
	MA(1)	1.626980	0.076968	21.13837	0.0000
	MA(2)	0.802706	0.072119	11.13028	0.0000
CAC–40	*AR(1)*	-0.031822	0.014142	-2.250210	0.0245
	AR(2)	0.736168	0.132926	5.538170	0.0000
	MA(2)	-0.748191	0.130739	-5.722779	0.0000
NIKEI–225	*AR(1)*	0.620847	0.201758	3.077180	0.0021
	MA(1)	-0.660501	0.193237	-3.418093	0.0006
IMKB–100	*AR(2)*	0.041630	0.018197	2.287696	0.0222

To test for the persistence of conditional heteroscedasticity, we calculated the Lagrange Multiplier test for ARCH effects. These results reported in Table-5. The LM test results validate the rejection of the homoskedasticity assumption for all series. In this respect, the GARCH class model seems to be the fitted model. The estimated parameters of the fitted GARCH class model are displayed in Table 6. (In Table 6 first parenthesis shows p value). The best volatility forecasting GARCH class models as an average of countries presented in Table 7. For determining the best forecast volatility model forecast model error terms as RMSE, MAE, and MAPE are used which is emphasized by Engle, and Patton, 2001; Hansen, and et all, 2003. In this context, the model which has minimum forecast error terms as RMSE, MAE, and MAPE, is the best volatility forecasting model.

Table 5: Lagrange-multiplier test results (ARCH LM Test)

The result of ARCH LM Test	
LM(2)FTSE–100$_F$	169.5600 (0,0000)
LM(2)AEX$_F$	1.680.393(0,0000)
LM(2)ATX$_F$	90.31525(0,0000)
LM(2)DAX$_F$	169.7871(0,0000)
LM(2)DJ$_F$	68.78761(0,0000)
LM(2)IPC$_F$	100.4147(0,0000)
LM(2)NASDAQ$_F$	104.5142(0,0000)
LM(2)SMI$_F$	150.2742(0,0000)
LM(2)CAC–40$_F$	114.2891(0,0000)
LM(2)NIKKEI–225	38.23787(0,0000)
LM(2)IMKB–100	90.74767(0,0000)

Table 6.1: GARCH models parametric estimates

	AEX[1]	*ATX*	*CAC–40*	*DAX*	*DJ*	*FTSE–100*	*İMKB–100*	*IPC*[2]	*NASDAQ*	*NIKEİ–225*	*SMI*
GARCH	*(2,1)*	*(1,1)*	*(2,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(2,2)*	*(1,1)*	*(2,2)*	*(1,1)*	*(1,1)*
ϖ	5.32E-08 (0.0000)	8.66E-08 (0.0000)	2.38E-08 (0.0000)	2.93E-08 (0.0001)	1.59E-08 (0.0000)	1.30E-08 (0.0009)	9.22E-10 (0.0232)	3.77E-08 (0.0001)	6.06E-08 (0.0000)	3.72E-08 (0.0000)	3.86E-08 (0.0000)
α_1	0.048283 (0.0166)	0.108916 (0.0000)	0.038095 (0.0099)	0.090817 (0.0000)	0.082984 (0.0000)	0.077312 (0.0000)	0.156192 (0.0000)	0.085980 (0.0000)	0.032887 (0.0138)	0.076517 (0.0000)	0.118553 (0.0000)
α_2	0.064932 (0.0035)	-	0.038731 (0.0202)	-	-	-	-0.146545 (0.0000)	-	0.119512 (0.0000)	-	-
β_1	0.876056 (0.0000)	0.846814 (0.0000)	0.915126 (0.0000)	0.900660 (0.0000)	0.907191 (0.0000)	0.914180 (0.0000)	1.629373 (0.0000)	0.903061 (0.0000)	0.278930 (0.0390)	0.908699 (0.0000)	0.860014 (0.0000)
β_2	-	-	-	-	-	-	-0.639191 (0.0000)	-	0.558171 (0.0000)	-	-
$LM(2)_F$	0.462518 (0.6297)	0.201720 (0.8173)	0.022457 (0.977793)	2.883865 (0.0561)	2.401477 (0.09075)	0.682203 (0.5056)	0.883567 (0.413413)	1.853716 (0.15683)	1.853716 (0.156830)	1.600977 (0.201867)	1.650911 (0.19204)
$LM(4)_F$	1.332692 (0.2553)	0.917208 (0.4528)	1.890913 (0.109230)	1.521166 (0.1932)	1.495134 (0.20090)	0.731540 (0.5703)	1.020457 (0.395232)	1.050902 (0.37934)	1.050902 (0.379346)	0.917961 (0.452380)	1.135590 (0.33777)
$LM(6)_F$	1.550199 (0.1577)	0.640147 (0.6982)	1.567423 (0.152488)	1.623936 (0.1363)	1.163179 (0.32310)	0.550963 (0.7696)	0.970826 (0.443285)	0.917991 (0.48066)	0.917991 (0.480661)	0.638905 (0.699192)	1.728132 (0.11036)
$LM(8)_F$	1.187759 (0.3021)	0.761292 (0.6371)	1.526619 (0.142476)	1.330704 (0.2231)	1.112226 (0.35135)	0.939819 (0.4820)	0.890199 (0.523715)	0.705750 (0.68678)	0.705750 (0.686780)	0.526728 (0.837219)	1.541504 (0.13751)
**RMSE*	0.002282	0.001429	0.001668	0.001795	0.001156	0.001257	0.001441	0.002221	0.002221	0.001483	0.001365
**MAE*	0.001554	0.001028	0.001208	0.001277	0.000828	0.000902	0.001020	0.001567	0.001567	0.001103	0.000957
**MAPE*	119.2898	150.3937	121.6969	120.9531	120.3046	114.9917	120.0294	118.9044	121.2946	107.9709	121.7335
Error distribution	GED	GED	Gaussian	GED	Gaussian	GED	Gaussian	GED	Gaussian	Gaussian	Gaussian

* For forecast model error term

[1] One outlier dummy is used for AEX for the lag of 1011.
[2] Three outlier dummies are used for IPC for the lags of 1011.705, 706, 923.

Table 6.2: TARCH models parametric estimates

	AEX[3]	*ATX*	*CAC–40*	*DAX*	*DJ*	*FTSE–100*	*İMKB–100*[4]	*IPC*[5]	*NASDAQ*[6]	*NIKEİ–225*	*SMI*
TARCH	*(1,1)*	*(1,1)*	*(1,1)*	*(2,1)*	*(2,1)*	*(2,1)*	*(2,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*
ω	4.39E-08 (0.0000)	9.67E-08 (0.0000)	2.42E-08 (0.0000)	4.39E-08 (0.0000)	1.50E-08 (0.0000)	1.45E-08 (0.0000)	1.20E-08 (0.0004)	3.30E-08 (0.0000)	2.32E-08 (0.0002)	3.65E-08 (0.0001)	3.44E-08 (0.0000)
α_1	0.024341 (0.0291)	0.038541 (0.0253)	0.022281 (0.0037)	-0.029370 (0.0024)	-0.061383 (0.0003)	-0.042030 (0.0427)	0.124449 (0.0000)	0.024401 (0.0000)	0.019490 (0.0244)	0.023787 (0.0092)	0.017170 (0.0720)
γ_1	0.113898 (0.0000)	0.107763 (0.0000)	0.078273 (0.0000)	0.103278 (0.0000)	0.114217 (0.0000)	0.117720 (0.0000)	0.009380 (0.3102)	0.104400 (0.0000)	0.082144 (0.0000)	0.084338 (0.0000)	0.132265 (0.0000)
α_2	-	-	-	0.087175 (0.0000)	0.070176 (0.0002)	0.043236 (0.0367)	-0.064017 (0.0027)	-	-	-	-
β_1	0.906384 (0.0000)	0.852239 (0.0000)	0.927733 (0.0000)	0.873674 (0.0000)	0.921651 (0.0000)	0.927530 (0.0000)	0.928245 (0.0000)	0.915731 (0.0000)	0.932418 (0.0000)	0.917831 (0.0000)	0.893684 (0.0000)
$LM(2)_F$	1.620715 (0.197926)	0.321036 (0.7254)	1.001643 (0.367396)	0.4472753 (0.63941)	0.6629273 (0.51541)	1.098786 (0.333407)	1.217303 (0.296173)	0.439962 (0.64410)	2.964594 (0.051730)	1.648368 (0.192533)	0.971158 (0.37876)
$LM(4)_F$	1.591328 (0.173774)	0.635470 (0.6372)	1.410994 (0.227642)	0.683116 (0.60360)	0.496352 (0.73844)	0.928480 (0.446255)	0.665952 (0.615614)	0.846599 (0.49548)	1.784709 (0.129033)	1.079166 (0.365045)	0.667202 (0.61473)
$LM(6)_F$	1.482385 (0.180019)	0.470181 (0.8309)	1.420508 (0.202633)	0.770652 (0.59293)	0.623582 (0.71159)	3.715477 (0.445879)	0.544187 (0.774859)	1.360464 (0.22681)	1.436335 (0.196635)	0.854369 (0.527849)	1.161233 (0.32418)
$LM(8)_F$	1.214716 (0.285835)	0.588736 (0.7880)	1.531679 (0.140773)	0.819376 (0.58537)	0.781365 (0.61917)	0.617178 (0.716761)	0.653036 (0.733284)	1.183517 (0.30477)	1.128293 (0.340455)	0.751109 (0.646239)	0.970063 (0.45743)
**RMSE*	0.002281	0.001428	0.001668	0.001798	0.001156	0.0012156	0.001405	0.001891	0.002176	0.001483	0.001364
**MAE*	0.0015556	0.001028	0.001209	0.001277	0.000828	0.000902	0.001009	0.001326	0.001555	0.001102	0.000958
**MAPE*	111.4789	140.5243	116.1370	114.4299	113.8920	106.4557	118.8309	123.3209	116.1436	102.4199	110.8817
Error distribution	Student's t	GED	GED	Student's t	Student's t	Student's t	Student's t	Gaussian	Student's	GED	Gaussian

* For forecast model error term

[3] One outlier dummy is used for AEX for the lag of 1011.
[4] Five outlier dummies are used for ISE-100 for the lags of 1512, 1463, 1462, 954, 923.
[5] Three outlier dummies are used for IPC for the lags of 705, 706, 923.
[6] Three outlier dummies are used for NASDAQ for the lags of 925, 1516, 1335.

Table 6.3: PARCH models parametric estimates

	AEX[7]	*ATX*	*CAC–40*	*DAX*	*DJ*	*FTSE–100*	*İMKB–100*	*IPC*[8]	*NASDAQ*[9]	*NIKEİ–225*	*SMI*
PARCH	(1,1)	(1,1)	(1,1)	(2,1)	(1,1)	(1,1)	(2,1)	(1,1)	(1,1)	(1,1)	(1,1)
ω	2.13E-07 (0.5760)	3.26E-06 (0.5539)	3.54E-06 (0.5003)	4.91E-08 (0.6306)	1.84E-05 (0.4650)	7.74E-06 (0.4631)	2.21E-08 (0.5175)	4.03E-08 (0.6162)	6.15E-08 (0.6343)	1.43E-05 (0.5100)	1.84E-05 (0.4811)
α_1	0.073209 (0.0000)	0.095152 (0.0000)	0.065518 (0.0000)	0.061455 (0.0181)	0.063138 (0.0000)	0.054949 (0.0000)	0.124983 (0.0000)	0.078592 (0.0000)	0.059112 (0.0000)	0.070298 (0.0000)	0.087930 (0.0000)
γ_1	0.422903 (0.0000)	0.400102 (0.0000)	0.475197 (0.0000)	0.273582 (0.0494)	0.807115 (0.0000)	0.852323 (0.0000)	0.032667 (0.1174)	0.317077 (0.0000)	0.348683 (0.0000)	0.530825 (0.0000)	0.610562 (0.0000)
α_2	-	-	-	0.032528 (0.2379)	-	-	-0.054470 (0.0093)	-	-	-	-
β_1	0.910129 (0.0000)	0.862460 (0.0000)	0.932114 (0.0000)	0.888361 (0.0000)	0.935071 (0.0000)	0.941523 (0.0000)	0.924103 (0.0000)	0.902302 (0.0000)	0.931401 (0.0000)	0.922786 (0.0000)	0.907974 (0.0000)
δ	1.758605 (0.0000)	1.464203 (0.0000)	1.258648 (0.0000)	1.958405 (0.0000)	0.990532 (0.0000)	1.090418 (0.0000)	1.924539 (0.0000)	1.989634 (0.0000)	1.850876 (0.0000)	1.115187 (0.0000)	1.053369 (0.0000)
$LM(2)_F$	2.028893 (0.131656)	0.192658 (0.8248)	0.395503 (0.673376)	2.062992 (0.12724)	0.658116 (0.51789)	0.20377 (0.815655)	1.481625 (0.227434)	0.301507 (0.73972)	2.994499 (0.050209)	1.238024 (0.290100)	0.439173 (0.64461)
$LM(4)_F$	2.114317 (0.076466)	0.563531 (0.6892)	1.28841 (0.272151)	1.334612 (0.25456)	0.395489 (0.81201)	0.41304 (0.799371)	0.817482 (0.513821)	0.722433 (0.57651)	1.728534 (0.140799)	1.142393 (0.334599)	0.455905 (0.76814)
$LM(6)_F$	1.774527 (0.100310)	0.399524 (0.8797)	1.437678 (0.196131)	1.224063 (0.29051)	0.359985 (0.90435)	0.321403 (0.926105)	0.6238916 (0.711340)	1.08311 (0.36997)	1.378830 (0.219175)	0.995044 (0.426744)	1.167855 (0.32050)
$LM(8)_F$	1.468086 (0.163485)	0.56997 (0.8033)	1.668302 (0.100975)	1.15323 (0.32399)	0.779178 (0.62113)	0.642662 (0.742295)	0.729549 (0.665535)	1.031602 (0.40946)	1.073833 (0.378322)	1.013619 (0.423168)	0.984962 (0.44555)
**RMSE*	0.002248	0.0014288	0.001668	0.001780	0.00116	0.0012156	0.001405	0.001892	0.002176	0.001482	0.001364
**MAE*	0.001546	0.001028	0.001209	0.001269	0.00082	0.000902	0.001009	0.001328	0.001555	0.001102	0.000958
**MAPE*	110.4243	139.2864	115.1003	114.3411	112.1677	105.3640	118.2203	125.3437	117.1577	101.2593	115.8186
Error distribution	Student's t	GED	GED	GED	GED	GED	Student's t	Student's t	Student's t	Gaussian	Student's t

* For forecast model error term

[7] Three outlier dummies are used for AEX for the lags of 1011, 2076, 2077.
[8] Three outlier dummies are used for IPC for the lags of 705, 706, 923.
[9] Three outlier dummies are used for NASDAQ for the lags of 925, 1516, 1335.

Table 6.4: CGARCH models parametric estimates

	AEX[10]	*ATX*	*CAC–40*	*DAX*	*DJ*	*FTSE–100*	*İMKB–100*[11]	*IPC*[12]	*NASDAQ*	*NIKEİ–225*	*SMI*
CGARCH	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*
ω	4.68E-06 (0.0007)	2.03E-06 (0.0000)	2.03E-06 (0.0003)	2.99E-06 (0.0000)	1.64E-06 (0.0000)	1.49E-06 (0.0003)	3.58E-06 (0.5809)	2.77E-06 (0.0001)	5.79E-06 (0.0275)	2.46E-06 (0.0003)	1.89E-06 (0.0000)
p_1	0.988403 (0.0000)	0.955329 (0.0000)	0.993246 (0.0000)	0.985809 (0.0000)	0.990064 (0.0000)	0.990491 (0.0000)	0.999590 (0.0000)	0.995794 (0.0000)	0.993832 (0.0000)	0.988359 (0.0000)	0.973170 (0.0000)
Φ_1	0.108150 (0.0000)	0.116114 (0.0000)	0.051262 (0.0000)	0.104250 (0.0000)	0.086401 (0.0000)	0.07888 (0.0000)	0.025523 (0.0000)	0.034522 (0.0000)	0.090786 (0.0000)	0.074005 (0.0000)	0.152507 (0.0000)
α_1	-0.060537 (0.0002)	0.014962 (0.0040)	-0.049453 (0.0079)	-0.077172 (0.0000)	-0.045019 (0.0000)	-0.002227 (0.0526)	0.106756 (0.0000)	0.085341 (0.0000)	-0.058753 (0.0000)	-0.099240 (0.0000)	-0.10427 (0.0000)
β_1	-0.098994 (0.7498)	-0.965888 (0.0000)	0.936719 (0.0000)	-0.067765 (0.8077)	-0.408750 (0.0887)	-0.995780 (0.0000)	0.784112 (0.0000)	0.806266 (0.0000)	-0.617310 (0.0000)	0.642035 (0.0001)	0.566070 (0.0001)
$LM(2)_F$	0.1783503 (0.836658)	0.0685413 (0.9338)	0.821975 (0.439659)	0.030887 (0.96958)	0.820024 (0.44051)	0.528442 (0.5896)	1.987450 (0.137224)	0.198186 (0.82022)	1.896816 (0.150222)	0.318362 (0.727364)	0.180510 (0.83485)
$LM(4)_F$	1.439449 (0.218265)	0.463652 (0.7625)	1.698758 (0.147426)	0.244494 (0.91309)	0.83885 (0.50031)	0.793615 (0.5292)	1.934310 (0.101990)	1.074467 (0.36739)	1.038871 (0.385563)	0.377040 (0.825174)	0.158078 (0.95939)
$LM(6)_F$	1.629421 (0.134797)	0.341336 (0.9152)	1.393018 (0.213421)	0.417492 (0.86784)	0.78651 (0.58038)	0.599591 (0.7309)	1.347416 (0.232372)	1.46892 (0.18475)	0.922943 (0.477085)	0.295249 (0.939418)	0.924788 (0.47575)
$LM(8)_F$	1.263251 (0.258127)	0.365494 (0.9389)	1.607116 (0.117383)	0.410618 (0.91512)	0.83886 (0.56820)	0.902840 (0.5130)	1.329893 (0.223500)	1.105637 (0.35589)	0.708446 (0.684378)	0.252132 (0.980444)	0.733268 (0.66220)
**RMSE*	0.002282	0.001429	0.001668	0.001799	0.001156	0.001257	0.001408	0.001895	0.002221	0.001483	0.001365
**MAE*	0.001555	0.001028	0.001209	0.001277	0.00082	0.000902	0.001010	0.001330	0.001568	0.001103	0.000958
**MAPE*	118.4128	147.9431	124.6481	116.7449	119.4615	112.6464	118.8964	140.7665	121.4513	108.2644	122.0940
Error distribution	Gaussian	Gaussian	GED	Gaussian	Gaussian	Gaussian	Gaussian	GED	Gaussian	Student's t	Gaussian

* For forecast model error term

[10] One outlier dummy is used for AEX for the lag of 1011.
[11] Four outlier dummies are used for ISE-100 for the lags of 925, 961, 1513, 1515.
[12] Three outlier dummies are used for IPC for the lags of 705, 706, 923.

Table 6.5: IGARCH models parametric estimates

	AEX[13]	*ATX*	*CAC–40*[14]	*DAX*	*DJ*	*FTSE–100*	*İMKB–100*	*IPC*	*NASDAQ*[15]	*NIKEİ–225*	*SMI*
IGARCH	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(1,1)*	*(2,2)*	*(1,1)*	*(2,1)*	*(1,1)*	*(1,1)*
α_1	0.077761 (0.0000)	0.076606 (0.0000)	0.055898 (0.0000)	0.069719 (0.0001)	0.061469 (0.0000)	0.063120 (0.0000)	0.126181 (0.0000)	0.064884 (0.0000)	0.026046 (0.0318)	0.057132 (0.0000)	0.072336 (0.0000)
α_2	-	-	-	-	-	-	-0.124529 (0.0000)	-	0.034908 (0.0097)	-	-
β_1	0.922239 (0.0000)	0.923394 (0.0000)	0.944102 (0.0000)	0.930281 (0.0000)	0.938531 (0.0000)	0.936880 (0.0000)	1.784170 (0.0000)	0.935116 (0.0000)	0.939047 (0.0000)	0.942868 (0.0000)	0.927664 (0.0000)
β_2	-	-	-	-	-	-	-0.785822 (0.0000)	-	-	-	-
$LM(2)_F$	0.092315 (0.9118)	1.460992 (0.2322)	0.717891 (0.4879)	1.020716 (0.3605)	2.082950 (0.1247)	1.183754 (0.3063)	2.070312 (0.1263)	1.974193 (0.1391)	0.843329 (0.6670)	0.685218 (0.5041)	0.059234 (0.9425)
$LM(4)_F$	0.532022 (0.7122)	2.162562 (0.0707)	1.720986 (0.1425)	0.820573 (0.5119)	1.666667 (0.1549)	1.184248 (0.3156)	1.827710 (0.1207)	2.122755 (0.0754)	2.301806 (0.0564)	0.537943 (0.7079)	1.100405 (0.3546)
$LM(6)_F$	0.464915 (0.8347)	1.497977 (0.1747)	1.606159 (0.1412)	1.364848 (0.2250)	1.180158 (0.3138)	0.890057 (0.5011)	1.376572 (0.2201)	1.995905 (0.0629)	0.757850 (0.9179)	0.417694 (0.8677)	1.847374 (0.0862)
$LM(8)_F$	0.366054 (0.9387)	1.432834 (0.1774)	1.373282 (0.2030)	1.102650 (0.3580)	1.071471 (0.3800)	1.180549 (0.3066)	1.326569 (0.2251)	1.595147 (0.1209)	1.410861 (0.1865)	0.327703 (0.9557)	1.649115 (0.1059)
**RMSE*	0.002410	0.001429	0.001662	0.001798	0.001157	0.001256	0.001436	0.001879	0.002186	0.001483	0.001372
**MAE*	0.001561	0.001028	0.001208	0.001277	0.000828	0.000901	0.001019	0.001318	0.001553	0.001103	0.000966
**MAPE*	113.9778	147.8756	119.4117	113.2616	119.6418	111.2798	121.6607	152.7373	132.0191	106.8403	144.2520
Error distribution	Gaussian	Gaussian	Gaussian	Gaussian	Gaussian	Gaussian	Gaussian	Gaussian	GED	Gaussian	Gaussian

* For forecast model error term

[13] Three outlier dummies are used for AEX for the lags of 1011, 2026, 2077.
[14] One outlier dummy is used for CAC–40 for the lag of 1680.
[15] Two outlier dummies are used for NASDAQ for the lags925, 1516.

Table 6.6: GARCH-M models parametric estimates

	AEX[16]	ATX	CAC–40	DAX	DJ	FTSE–100	İMKB–100	IPC[17]	NASDAQ	NIKEİ–225	SMI
GARCH-M	(2,1)	(1,1)	(2,1)	(1,1)	(1,1)	(1,1)	(2,2)	(1,1)	(2,2)	(1,1)	(1,1)
ϖ	5.32E-08 (0.0000)	8.64E-08 (0.0000)	2.38E-08 (0.0000)	2.93E-08 (0.0001)	1.62E-08 (0.0000)	1.31E-08 (0.0009)	5.82E-10 (0.0663)	3.50E-08 (0.0001)	6.26E-08 (0.0000)	3.73E-08 (0.0000)	3.96E-08 (0.0000)
α_1	0.050512 (0.0137)	0.108069 (0.0000)	0.038343 (0.0103)	0.090813 (0.0000)	0.083628 (0.0000)	0.077514 (0.0000)	0.155229 (0.0000)	0.081591 (0.0000)	0.034691 (0.0108)	0.076551 (0.0000)	0.119153 (0.0000)
α_2	0.063120 (0.0050)	-	0.038413 (0.0226)	-	-	-	-0.148496 (0.0000)	-	0.120471 (0.0000)	-	-
β_1	0.875765 (0.0000)	0.847707 (0.0000)	0.915211 (0.0000)	0.900664 (0.0000)	0.906285 (0.0000)	0.913946 (0.0000)	1.671613 (0.0000)	0.908297 (0.0000)	0.287840 (0.0409)	0.908634 (0.0000)	0.858850 (0.0000)
β_2	-	-	-	-	-	-	-0.678494 (0.0000)	-	0.546179 (0.0000)	-	-
λ	0.020854 (0.6710)	0.057522 (0.4779)	0.025651 (0.6462)	0.008583 (0.8660)	0.093772 (0.1172)	0.035135 (0.5201)	0.041387 (0.4235)	-0.030797 (0.5754)	0.048428 (0.3045)	0.006495 (0.9303)	0.123213 (0.0332)
$LM(2)_F$	0.407743 (0.6652)	0.182581 (0.8331)	0.016925 (0.983217)	2.887314 (0.0559)	2.569517 (0.07673)	0.652098 (0.5210)	0.849405 (0.427772)	0.67444 (0.50951)	1.708258 (0.181354)	1.606245 (0.200807)	1.69596 (0.18359)
$LM(4)_F$	1.291959 (0.2708)	0.921650 (0.4502)	1.906743 (0.106533)	1.522848 (0.1927)	1.573664 (0.17849)	0.708316 (0.5862)	1.187178 (0.314306)	1.381660 (0.23767)	0.962577 (0.426807)	0.921173 (0.450503)	1.099103 (0.35521)
$LM(6)_F$	1.522470 (0.1665)	0.650408 (0.6899)	1.582451 (0.148023)	1.630002 (0.1346)	1.229675 (0.28764)	0.538411 (0.7794)	0.982099 (0.435541)	1.5549281 (0.15629)	0.856638 (0.526130)	0.640746 (0.697700)	1.728132 (0.11036)
$LM(8)_F$	1.171032 (0.3126)	0.762639 (0.6359)	1.555269 (0.133061)	1.336179 (0.2204)	1.208273 (0.28967)	0.940796 (0.4812)	0.946086 (0.476896)	1.345082 (0.21613)	0.661107 (0.726236)	0.527981 (0.836268)	1.527767 (0.14209)
*RMSE	0.002283	0.001430	0.001668	0.001799	0.001158	0.001257	0.001442	0.001891	0.002223	0.001483	0.001365
*MAE	0.001554	0.001028	0.001208	0.001277	0.000829	0.000902	0.001021	0.001326	0.001567	0.001103	0.001366
*MAPE	124.5608	156.5167	125.0885	122.1151	134.4334	118.6476	125.1000	129.0377	133.1722	108.5337	0.000957
Error distribution	GED	GED	Gaussian	GED	Gaussian	GED	Gaussian	GED	Gaussian	Gaussian	Gaussian

* For forecast model error term

[16] One outlier dummy is used for AEX for the lag of 1011.
[17] Three outlier dummies are used for IPC for the lags of 705, 706, 923.

Table 6.7: EGARCH models parametric estimates

	AEX[18]	*ATX*	*CAC–40*	*DAX*	*DJ*	*FTSE–100*	*İMKB–100*[19]	*IPC*[20]	*NASDAQ*	*NIKEİ–225*	*SMI*
EGARCH	*(2,1)*	*(1,1)*	*(1,1)*	*(2,1)*	*(1,1)*	*(1,1)*	*(2,2)*	*(1,1)*	*(2,1)*	*(1,1)*	*(1,1)*
ω	-0.366885 (0.0000)	-0.768126 (0.0000)	-0.267529 (0.0000)	-0.453534 (0.0000)	-0.343157 (0.0000)	-0.270842 (0.0000)	-0.103651 (0.0048)	-0.328151 (0.0000)	-0.328545 (0.0000)	-0.399787 (0.0000)	-0.38614 (0.0000)
α_1	0.061952 (0.0494)	0.186124 (0.0000)	0.128620 (0.0000)	0.016084 (0.6820)	0.119541 (0.0000)	0.106018 (0.0000)	0.290484 (0.0000)	0.162209 (0.0000)	0.058559 (0.0801)	0.135690 (0.0000)	0.140944 (0.0000)
α_2	0.109881 (0.0004)	-	-	0.169547 (0.0001)	-	-	-0.217766 (0.0000)	-	0.089760 (0.0138)	-	-
γ_1	-0.072046 (0.0000)	-0.081877 (0.0000)	-0.065536 (0.0000)	-0.079905 (0.0000)	-0.090413 (0.0000)	-0.088286 (0.0000)	0.003571 (0.2229)	-0.090375 (0.0000)	-0.082615 (0.0000)	-0.074616 (0.0000)	-0.09888 (0.0000)
β_1	0.981591 (0.0000)	0.953101 (0.0000)	0.987321 (0.0000)	0.976382 (0.0000)	0.981886 (0.0000)	0.986396 (0.0000)	1.452528 (0.0000)	0.984213 (0.0000)	0.983136 (0.0000)	0.977607 (0.0000)	0.979695 (0.0000)
β_2	-	-	-	-	-	-	-0.456138 (0.0016)	-	-	-	-
$LM(2)_F$	0.860158 (0.4232)	0.124436 (0.8830)	0.243710 (0.783730)	0.933113 (0.39343)	0.823294 (0.43908)	0.148852 (0.8617)	1.636683 (0.194798)	1.035724 (0.35509)	2.747409 (0.064252)	1.110025 (0.329682)	0.237047 (0.78896)
$LM(4)_F$	1.398401 (0.2319)	0.595627 (0.6658)	1.244875 (0.289657)	0.680528 (0.60540)	0.511980 (0.72694)	0.356264 (0.8398)	0.832755 (0.504149)	1.232610 (0.29475)	1.511219 (0.196117)	1.041297 (0.384301)	0.247266 (0.91142)
$LM(6)_F$	1.414704 (0.2049)	0.402428 (0.8778)	1.411052 (0.206291)	2.052001 (0.05569)	0.467470 (0.83284)	0.279271 (0.9469)	0.818050 (0.555723)	1.800755 (0.09500)	1.373607 (0.221324)	0.971894 (0.442543)	0.989366 (0.43058)
$LM(8)_F$	1.119899 (0.3461)	0.634968 (0.7489)	1.688014 (0.096138)	1.823230 (0.06816)	0.814478 (0.58971)	0.592328 (0.7850)	0.850682 (0.557861)	1.509545 (0.14835)	1.098243 (0.361025)	0.966791 (0.460062)	0.862938 (0.54719)
**RMSE*	0.002282	0.001428	0.001668	0.001793	0.001156	0.001256	0.001405	0.001892	0.002221	0.001482	0.001370
**MAE*	0.001556	0.001028	0.001209	0.001275	0.000828	0.000902	0.001011	0.001328	0.001556	0.001102	0.000962
**MAPE*	106.3718	136.2870	116.1158	109.3820	114.7857	107.0952	120.5036	115.00209	122.5997	100.1904	135.1870
Error distribution	Gaussian	GED	Student's t	GED	GED	GED	Gaussian	Student's t	Gaussian	GED	GED

* For forecast model error term

[18] One outlier dummy is used for AEX for the lag of 1011.
[19] Five outlier dummies are used for ISE-100 for the lags of 925, 961, 1465, 1466, 1515.
[20] Three outlier dummies are used for IPC for the lags of 705, 706, 923.

Table.7: The best volatility forecasting GARCH class model (as an average of countries)

	the best forecasting model → the worst forecasting model						
AEX	PARCH	E-GARCH	TARCH	IGARCH	C-GARCH	GARCH	GARCH-M
ATX	E-GARCH	PARCH	TARCH	GARCH	IGARCH	C-GARCH	GARCH-M
CAC–40	PARCH	E-GARCH	TARCH	IGARCH	GARCH	C-GARCH	GARCH-M
DAX	E-GARCH	PARCH	IGARCH	TARCH	C-GARCH	GARCH	GARCH-M
DJ	PARCH	TARCH	E-GARCH	C-GARCH	IGARCH	GARCH	GARCH-M
FTSE–100	PARCH	TARCH	E-GARCH	IGARCH	C-GARCH	GARCH	GARCH-M
İMKB–100	E-GARCH	PARCH	TARCH	C-GARCH	GARCH	IGARCH	GARCH-M
IPC	E-GARCH	GARCH	TARCH	PARCH	GARCH-M	C-GARCH	IGARCH
NASDAQ	TARCH	PARCH	C-GARCH	GARCH	E-GARCH	IGARCH	GARCH-M
NIKEİ–225	E-GARCH	PARCH	TARCH	IGARCH	GARCH	C-GARCH	GARCH-M
SMI	TARCH	PARCH	GARCH	C-GARCH	E-GARCH	GARCH-M	IGARCH
The best model as an average	E-GARCH	PARCH	TARCH	IGARCH	C-GARCH GARCH	C-GARCH GARCH	GARCH-M

5. Conclusion

In this study seven different GARCH class models employ to forecast in-sample of daily stock market volatility in 10 different countries. Also daily returns are used for the period ranging from the 1th of January 1995 to the 31th of February 2007. For this purpose, firstly the stationarity of the series is tested by ADF unit root test; For all the series, the null hypotheses of unit root were rejected. Secondly, for modeling the conditional mean, we detected to fitted AR, MA, ARMA for all countries stock exchange markets. Thirdly, the seven GARCH class model was estimated for modeling the conditional volatility of all stock markets, since the LM test results validate the rejection of the homoskedasticity assumption.

The findings of study emphasize the best forecast volatility models are differ for countries structure, but as an average from the best forecast volatility model to the worst forecast volatility model is ranging as E-GARCH, PARCH, TARCH, IGARCH, C-GARCH, GARCH, C-GARCH, GARCH, GARCH-M which shows that the class of asymmetric volatility models perform better in forecasting of stock market volatility than the historical model which is supported in the literature (Franses ve Dijk, 1996; Maris and et all., 2004; Loudan, Watt ve Yadav, 2000).

Volatility is widely used as simple risk measures in many asset pricing models. Additionally volatility enters option pricing formulas derived from Black-Schools models and its various extensions. For hedging against risk, portfolio management consistent volatility forecast is curial.

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