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SYMMETRIC AND ASYMMETRIC VOLATILITY: FORECASTING THE BORSA ISTANBUL 100 INDEX RETURN VOLATILITY

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Abstract

The development of technology and the globalization of financial markets have increased the volatility in financial markets and caused the emergence of risks and uncertainties that have not been previously encountered. Since traditional econometric models cannot fully explain this volatility, nonlinear conditional variance models such as ARCH, GARCH, EGARCH and TARCH are used today. From this point of view, this study aims to determine the most explanatory model that fund managers who are considering investing in the Borsa Istanbul 100 (BIST 100) Index, and academicians doing research on this subject, can use in estimating the BIST 100 Index return volatility. For this purpose, ARCH and GARCH models, as symmetric models, and EGARCH and TARCH models, as asymmetric nonlinear conditional models, are included in the econometric analysis by using the end-of-day values of 2657 observations belonging to the 04.01.2010-28.07.2020 period. According to the empirical results of the study, the TARCH model, which has the highest level of explanatory power, gives the most successful results among related models in revealing BIST 100 Index return volatility.

JEL classification: C58, F30, F37
Keywords: ARCH models, symmetric volatility, asymmetric volatility

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Introduction

The end of fixed exchange rate regimes in the 1970s led to unprecedented uncertainties in financial markets. These uncertainties caused the risk in all financial products to increase. Thus the concept of risk in financial markets and the volatility created by this risk concept have been one of the most frequently studied issues.

Previously, standard deviation, which shows how far each value in the distribution is from the mean, was used to detect volatility. In this method, it is assumed that the variance does not change over time. However, the use of fixed variance in a financial series can give the wrong results in today's financial markets. It has been observed that variance, which is a measure of volatility, varies depending on time in a financial time series, and models based on fixed variance have begun to fail to meet the needs. Therefore, the increasing importance of risk and uncertainty in today's financial markets has necessitated the development of econometric time series that enable the modelling of variance and covariance depending on time.

In this direction, the Autoregressive Conditional Heteroskedasticity (ARCH) model was developed by Engle (1982) to estimate the variance that changes over time. The unconditional variance was assumed to be constant in the model (Engle, 1982; Engle & Ng, 1993).

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which is the most widely used financial volatility forecasting model in finance, was developed by Engle and Bollerslev in 1986 (Engle & Bollerslev, 1986). The model in question is a method that not only measures volatility, but also shows whether shocks on volatility are continuous (Kıran, 2010). The GARCH model is slightly different from the ARCH model. The reason for this is that the ARCH model was put forward to alleviate some of its problems, such as not being able to fully explain the variance behaviour and predicting volatility much larger than it should be due to the slow response to major shocks (Kayalıdere, 2013).

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model was developed by Nelson in 1991 in order to explain the asymmetrical volatility structure observed in financial markets. According to this study, researchers have found evidence that stock returns are negatively correlated with changes in return volatility. In other words, volatility tends to rise in response to "bad news" (excess returns lower than expected) and to fall in response to "good news" (excess returns higher than expected). GARCH models, however, assume that only the magnitude and not the positivity or negativity of unanticipated excess returns effect the conditional variance. In the model developed by Nelson, the conditional variance may vary depending not only on the magnitude of the shock, but also on the sign. This suggests that a model in which the conditional variance responds asymmetrically to positive and negative residuals might be preferable for asset pricing studies (Nelson, 1991). Moreover, according to Nelson's study, negative shocks of the same size have a greater effect on volatility than positive shocks (Yaman & Koy, 2019).

Another important model that takes into account the asymmetric volatility structure is the Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model which was developed by Zakoian in 1994. In the model developed by Zakoian, the conditional standard deviation is a piecewise linear function of past values of the white noise, and this specific form provides different reactions of the volatility to different signs of the lagged errors (Zakoian, 1994). The conditional variance in this model is a sign function and can be used to model the structure in different directions and magnitudes. In this case, if the coefficient of the new variable is statistically significant, the ARCH effect will appear in the conditional variance (Kızılsu et al., 2001).

The aim of this study is to determine the model that best explains the return volatility of the Borsa Istanbul 100 (BIST 100) Index. The BIST 100 Index is the main indicator used to measure the performance of the top 100 stocks traded in Borsa Istanbul in terms of market and trading volume, and is carefully followed by all major investors.

Literature review

Before the econometric analysis regarding the determination of the model that best explains the return volatility of the BIST 100 Index, it will be useful to examine the symmetric and asymmetric models used in the estimation of the BIST 100 Index and the stock market indices of other countries.

In one of these studies, Akar (2007) compares the volatility forecasting performances of alternative estimation models by using weekly closing values of the Istanbul Stock Exchange 100 (ISE 100) Index for the period of 05.01.1990-10.08.2007. The return volatility forecasts of ARCH, GARCH and SWARCH models are compared with actual volatility values, and forecasting performances are evaluated employing assorted error statistics. According to the analysis results, it is observed that the SWARCH model gives better results than the ARCH and GARCH models in terms of the forecasting performance of the volatility estimation models. From this point of view, it is suggested in the study it is suggested in the study that investors and portfolio managers should consider the SWARCH model as a good alternative when forecasting volatility.

Alberg et al. (2008) perform a comprehensive empirical analysis of the mean return and conditional variance of the Tel Aviv Stock Exchange (TASE) indices in order to investigate the forecasting performance of GARCH, EGARCH, GJR and APARCH models together. The prediction performance of the GARCH and EGARCH conditional changing variance models is compared to newer asymmetric GJR and APARCH models in the study. As a result of the empirical analysis using the data which consist of 3058 daily observations of the TA251 Index from the 20.10.1992-31.05.2005 period and 1911 daily observations of the TA1002 Index from the 02.07.1997-31.05.2005 period, it is stated that the asymmetric GARCH model with fat-tailed densities improves overall estimation for measuring conditional variance. They also indicate that the EGARCH model using a skewed Student-t distribution is the most successful for forecasting TASE indices.

Atakan (2009) investigates the most appropriate method for modelling the volatility at the Istanbul Stock Exchange (ISE) by using 5157 daily closing data of the ISE 100 Index belonging to the 03.07.1987-18.07.2008 period. According to the analysis results, it is observed that the volatility of the ISE 100 Index has the ARCH effect and the most appropriate model for forecasting the volatility of the ISE 100 Index is the GARCH (1,1) model.

Wong and Cheung (2011) use GARCH family models to study the evolution of stock price volatility in the Hong Kong stock market for the 1984-2009 period. The fluctuations of the Shanghai A-Share Price Index, the change of crude oil prices and interest rate movement are examined in the study as the variables that may lead to the volatility of the Hong Kong stock market. Moreover, the News Impact Curve is built to compare the impact of news on the volatility of the stock return, and this analysis implies that there is an asymmetric effect on the Hang Seng daily returns. Empirical results also show that both EGARCH and AGARCH models can detect the asymmetric effect well, in response to both good news and bad news, and the best estimation model for the Hong Kong stock market is the EGARCH model.

Tripathy and Garg (2013) forecast the stock market volatility of six emerging countries, namely Brazil, Russia, Mexico, India, China and South Africa, by using the ARCH, GARCH, GARCH-M, EGARCH and TGARCH models and daily observations of indices over the January 1999 -May 2010 period. Results of the analysis reveal that (i) there is a positive relationship between stock return and risk only in the Brazilian stock market, (ii) the volatility shocks are quite persistent in all countries' stock markets, (iii) the asymmetric GARCH models find significant evidence of asymmetry in all countries' stock markets, (iv) there is a leverage effect in the return series and bad news generates more impact on the volatility of the stock price in the market, (v) volatility increases disproportionately with negative shocks in the stock returns. According to these results, investors are advised to use investment strategies analysing recent and historical news and forecast the future market movement while selecting a portfolio, and policy makers of all these emerging countries are advised to have some degree of convergence of stock market rules and regulations and institutional arrangement so that investors can be able to get diversified portfolio returns.

Karabacak et al. (2014) aim to define the most appropriate conditional heteroscedasticity models for modelling the volatility of the BIST 100 Index and gold returns by using daily closing values of the BIST 100 Index for the 03.01.2003-11.09.2013 period and the weighted average prices of daily gold exchange transactions for the 03.01.2005-10.09.2013 period. According to the results of the study, (i) there are some asymmetric effects on the volatility of the BIST 100 Index return, (ii) the most appropriate model for estimating the volatility of the BIST 100 Index return is TARCH(1,1), and (iii) the most appropriate model for estimating the volatility of gold returns is GARCH(1,1).

Joshi (2014) uses three different models to forecast daily volatility of the Sensex of the Bombay Stock Exchange of India for the 01.01.2010-04.07.2014 period: GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1). According to the results of the study, (i) the volatility in the Sensex exhibits the persistence of volatility, mean reverting behaviour and volatility clustering, (ii) there is a leverage effect implying impact of good and bad news is not same, and (iii) the best forecasting model is GARCH(1,1).

Jha and Singh (2014) investigate two main issues in the study. The first one of them is the effects of four macroeconomic variables (interest rate, exchange rate, money supply, and net inflows of foreign institutional investors) on Indian stock markets which is represented by the Bombay Stock Exchange (BSE) SENSEX Index. The variables used in the analysis are monthly observations for the January 2000-December 2008 period. The results of the analysis indicate that there are comovements between stock market index and macroeconomic variables in a long-run equilibrium path, and the variations in the stock prices are mainly attributed to its own variations and to a smaller extent to other macroeconomic variables. The second aim of the study is to forecast the volatility of stock markets which is represented by NIFTY's weekly index over the time pe-

period from 07.07.2008 to 29.12.2008 with the help of ARCH models. The results of the analysis indicate that the EGARCH model is the best forecasting model here.

Birău, Trivedi and Antonescu (2015) aim to model the volatility patterns of the S&P Bombay Stock Exchange (BSE) BANKEX Index. The financial data series consist of daily closing asset prices for the selected stock index during the January 2002-June 2014 period, and GARCH(1,1) model is used to capture asymmetric volatility clustering and leptokurtosis. Empirical findings reveal that there are volatility shocks in series and volatility clusters. Moreover, the BANKEX index has grown over 17 times in 12 years and volatility returns have been found present in the listed stocks.

Qamruzzaman (2015) compares the forecasting performance of several GARCH family models. The comparison focuses on two different aspects: the difference between symmetric and asymmetric GARCH (i.e., GARCH versus EGARCH, GJR and APARCH) and the difference between normal tailed symmetric, fat-tailed symmetric and fat-tailed asymmetric distributions (i.e. Normal versus Student-t and Skewed Student-t). The data used in the empirical analysis includes the Chittagong Stock Exchange (CSE) Index return values for the 01.01.2004-14.09.2014 period. The results of the analysis reveal that there is volatility clustering in the return values of the CSE Index, and EGARCH-z, IGARCH-z, GJR-GARCH-z and EGARCH-t asymmetric models may be best suited for capturing CSE Index return volatility.

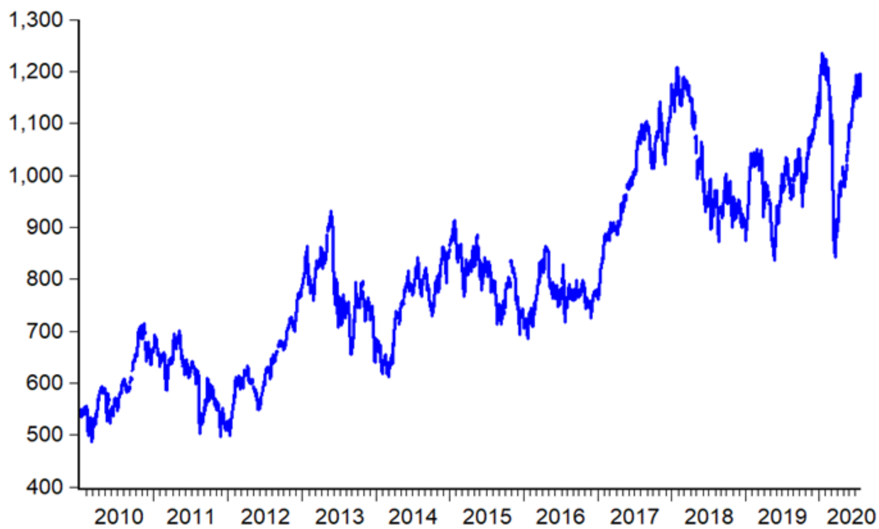
Tamilselvan and Vali (2016) aim to forecast the stock market volatility of four actively trading indices of the Muscat security market by using daily observations of indices belong to the January 2001-November 2015 period. The symmetric GARCH(1,1) model, and the asymmetric EGARCH(1,1) and TGARCH(1,1) models are used in the empirical analysis. According to the results of the study, (i) there is a positive relationship between risk and return, (ii) the volatility shocks are quite persistent, (iii) the asymmetric EGARCH(1,1) and TGARCH (1,1) models find significant evidence of an asymmetrical relationship between return shocks and volatility adjustments and the leverage effect is found across all flour indices, and (iv) the investors should formulate investment strategies by analysing recent and historical news and forecast the future market movements while selecting a portfolio for an efficient financial management.

Kuzu (2018) emphasizes the importance of estimating volatility in financial markets which is one of the most important factors in the decision making process especially in developing countries that are more fragile than developed countries. From this point of view, the study aims to analyse the return volatility of the BIST 100 Index by using ARCH, GARCH, EGARCH and TGARCH models. As a result of the empirical analysis using daily closing values belonging to the 2011-2017/3 period, it is observed that the TGARCH model, which has the highest level of explanatory power, gives the most successful results among related models in revealing BIST 100 Index return volatility.

Data and methodology

The data used in the econometric model of the study is the end-of-day values of 2657 observations belonging to the 04.01.2010-28.07.2020 period. The data set was obtained from Bloomberg Data Distribution Services and E-Views 8 econometrics analysis program was used in the empirical analysis.

Figure 1: The value of the BIST 100 Index



Source: Authors' elaboration.

Figure 1 illustrates the changes observed in the closing values of the BIST 100 Index during the data period. BIST 100 Index return volatility is found by dividing the difference between two closing values by the first closing value. In other words, the return volatility of the BIST 100 Index is determined by calculating the percentage increase or decrease in the daily return of the index. But before proceeding to the analysis, the stationarity of the series in the examined period should be examined. As it is known, models created with non-stationary data do not give realistic results. Therefore, it is important for the series to be stationary in order to obtain statistically reliable results. In other words, the series to be used in the analysis with ARCH and GARCH models should be stationary and not include unit root. The concept of stationarity is that the first and second moments of a stochastic process do not change over time. Therefore, series with stationary characteristics are series with constant mean, variance and covariance for each lag period (Gujarati, 2003).

As the first step of the analysis, the statistical data on the returns of the BIST 100 Index over daily closing prices are presented in Table 1. Accordingly, the kurtosis value is 2.2757, and greater than 3 (excess of flattening). The skewness value is 0.3415, and different from zero. This positive value of the skewness indicates that the distribution of the variables is skewed. In econometric analysis, an excess of flattening corresponds a sharp distribution, while the skewness of the distribution is positive if the tail is longer. In our sample, when Figure 1 and Table 1 are examined, it is concluded that the series do not move around the mean. Therefore, the series can contain unit root. The purpose of unit root testing is that ARCH and GARCH models need a stationary time series.

Table 1: Descriptive statistics of the BIST 100 Index

Statistics	BIST 100 Index
Mean	810.640500
Median	785.360000
Maximum	1235.560000
Minimum	487.390000
Std. Dev.	176.435300
Skewness	0.341530
Kurtosis	2.275785
Jarque-Bera	109.718400
P-Value	0.000000
Observations	2657.000000

Source: Calculated by the authors in E-Views 8.

In this study, the stationarity of the series is examined with the Augmented Dickey-Fuller (ADF) unit root test, which is the most widely used method in analyses (Dickey & Fuller, 1979; Dickey & Fuller, 1981). Phillips-Perron (PP) unit root test (Philips & Perron, 1988) is also applied in order to support the results of the ADF unit root test.

Two hypotheses used to test the existence of a unit root are as follows:

$$H_0 : \gamma = 0 \,(p = 1) \tag{1}$$

There is a unit root in the series.

$$H_1 : \gamma < 0 \,(p < 1) \tag{2}$$

There is no unit root in the series.

If the H_0 hypothesis is rejected, it is concluded that the Y variable is stationary, and if the H_0 hypothesis cannot be rejected, the Y variable is not stationary. At this point, the difference is taken until stationarity is achieved (Nur & Ege, 2019).

Empirical results

The ADF and PP unit root test statistics of the returns of the BIST 100 Index are given in Table 2. Accordingly, the probability values corresponding to the t-statistics are over the MacKinnon 5% critical value (MacKinnon, 1996). Therefore, the H_0 hypothesis cannot be rejected, and this means that the BIST 100 Index return series are not stationary in level values.

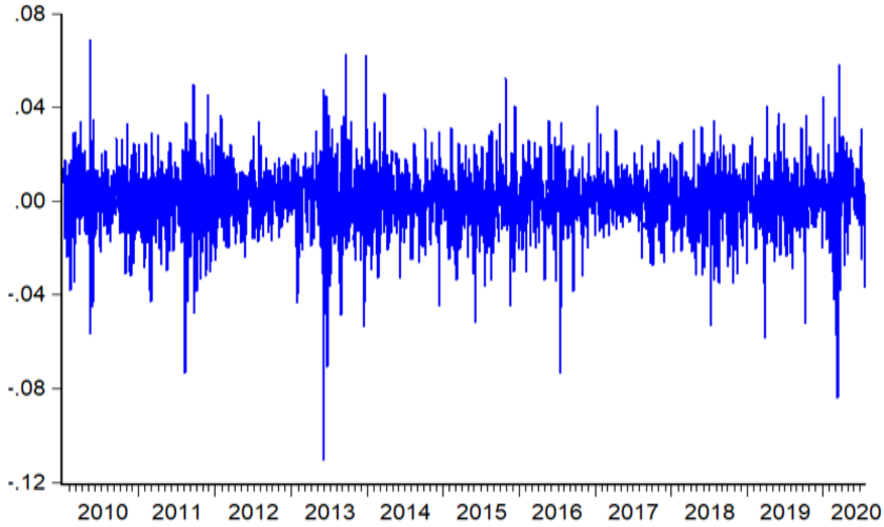
Table 2: Unit root test statistics

Variables			Intercept	Trend & Intercept	Result
BIST100 Index	ADF	Level	0.8674	0.7577	I(0)
		1st Difference	0.0001	0.0000	I(1)
	PP	Level	0.8643	0.7566	I(0)
		1st Difference	0.0001	0.0000	I(1)

Source: Calculated by the authors in E-Views 8.

On the other hand, the probability values corresponding to the t-statistics of the first difference of the series are below the MacKinnon 5% critical value. Therefore, the H_0 hypothesis is rejected, and this means that there is no unit root problem and the BIST 100 Index return series are stationary in the first difference values. Thus, the series became suitable for ARCH and GARCH models. Figure 2 illustrates the changes observed in the values of the BIST 100 Index without a unit root.

Figure 2: The value of the 1st difference of BIST 100 Index



Source: Calculated by the authors in E-Views 8.

As the next step in the analysis, the ARCH-LM test and the White test were applied in order to check whether there is variance and autocorrelation in the BIST 100 Index. ARIMA models were tested in different degrees and the most suitable model was determined for the structure of the series. The first step of the ARCH-LM test is to decide on the mean equation (Özer & Ece, 2016). ARCH-LM and White test results are given in Table 3.

Table 3: ARCH-LM and White test results

Variables		ARCH-LM
DLOGBIST 100	F-Statistics	26.2349
	Obs R-square	25.9975
	Probability	0.0000
		WHITE TEST
	F-Statistics	21.6621
	Obs R-square	42.6760
	Probability	0.0000

Source: Calculated by the authors in E-Views 8.

According to ARCH-LM and White test results in Table 3, it was concluded that there is variance and autocorrelation in BIST 100 Index returns. Therefore, it can be said that BIST 100 Index returns are suitable for ARCH and GARCH modelling.

Table 4: Statistical results of the models

	ARCH (1,1)	GARCH (1,1)	EGARCH (1,1)	TARCH (1,1)
R2	-0.000745	-0.001601	-0.000377	-0.000361
AIC	-5.668027	-5.750417	-5.775212	-5.776006
SIC	-5.659162	-5.739336	-5.761914	-5.762708
Hannan-Qui Cri	-5.664819	-5.746406	-5.770399	-5.771193
Log like	-7528.306000	-7638.679000	-7672.593000	-7673.647000

Source: Calculated by the authors in E-Views 8.

Table 4 reveals the econometric analysis results of the study. According to the results, since the TARCH model is the model with the highest R^2 value and the lowest Akaike, Schwarz, Log Likelihood information criterias, it was determined that the TARCH model is the most suitable among the related models.

Conclusions

The development of technology and the globalization of financial markets have increased the volatility in financial markets and caused the emergence of risks and uncertainties that have not been previously encountered. Therefore, it is vital to find out which of the estimation models can best explain stock return volatility. Since traditional econometric models cannot fully explain this volatility, nonlinear conditional variance models such as ARCH, GARCH, EGARCH and TARCH are used today.

ARCH and GARCH models are symmetric models which assume that only the magnitude and not the positivity or negativity of unanticipated excess returns effect the conditional variance. But researchers have found evidence that stock returns are negatively correlated with changes in return volatility. In other words, volatility tends to rise in response to "bad news" (excess returns lower than expected) and to fall in response to "good news" (excess returns higher than expected). From this point of view, Nelson developed an asymmetric model in 1991, namely the EGARCH model, in which the conditional variance may vary depending not only on the magnitude of the shock, but also on the sign. This suggests that a model in which the conditional variance responds asymmetrically to positive and negative residuals might be preferable for asset pricing studies. These findings were followed by another important model that takes into account the asymmetric volatility structure. This model is the TARCH model which was developed by Zakoian in 1994.

The aim of this study is to determine the model that best explains the return volatility of the Borsa Istanbul 100 (BIST 100) Index. The BIST 100 Index is the main indicator used to measure the performance of the top 100 stocks traded on Borsa Istanbul in terms of market and trading volume, and is carefully followed by all major investors. For this purpose, ARCH and GARCH models as symmetric models and EGARCH and TARCH models as asymmetric nonlinear conditional models are included in the econometric analysis by using the end-of-day values of 2657 observations belonging to the 04.01.2010-28.07.2020 period. According to the empirical results of the study, the TARCH model, which has the highest level of explanatory power, gives the most successful results among related models in revealing BIST 100 Index return volatility. Therefore, we suggest that fund managers who are considering investing in the Borsa Istanbul 100 (BIST 100) Index, and academicians doing research on this subject, can use the asymmetric TARCH model in estimating the BIST 100 Index return volatility.

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