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RESEARCH ARTICLE

Analysis of Istanbul Stock Market Returns Volatility with ARCH and GARCH Models

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ABSTRACT

In today's world where globalization is intensely experienced, differences in risk perception, developments in capital markets, and the negativities faced in the markets due to uncertainty are very important when researching the structures of the stock markets, and therefore determining current volatilities. One of the biggest problems encountered is the inability to price stocks effectively. Therefore, estimating and modeling volatility becomes crucial. The diversity of the portfolio, created by international investors in the financial markets and the sustainability of their investment decisions, are closely related to the volatility variable. However, the fact that financial markets are more fragile in developing countries increases the importance of volatility. There are many different methods in the literature when estimating volatility. Due to the inadequacy of traditional time series models in estimating volatility, conditional heteroskedasticity models are used with ARCH and GARCH class models being frequently used. In this study, the series of daily opening values of the ISE100 Index covering from 02.01.2003 to 30.09.2022 was estimated using ARCH/GARCH models for volatility with the aim to determine which model has the higher explanatory power. According to the findings, the GARCH(1,1) model gave more meaningful results in explaining the ISE100 return volatility.

Keywords: Volatility, Conditional Heteroskedasticity Models, Istanbul Stock Market
JEL Classification: E00, C53, D53

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1. Introduction and Conceptual Framework

Volatility is a concept that appears in many areas of economic theory, especially in financial markets. In many models of financial markets, volatility is used as the main variable because volatility is of great importance to investors. In its most general form, volatility means that a variable takes very high or very low values compared to its average value and is considered an indicator of macroeconomic stability.

Volatility is accepted as a measure of price change in various markets for the period under consideration. That is, it can be defined as the standard deviation of the change in the logarithm of the price or price index within a certain period (Taylor, 2005, p.189). In the literature, the stock market is a concept that is often encountered in exchange rates, inflation, crypto money, and similar variables. Volatility is shaped by the concepts of volatility on the one hand and uncertainty on the other. While variability covers all movements, the concept of uncertainty refers to unknown movements (Çiçek, 2010, p. 2).

The importance of volatility can also be associated with its use as a risk measure. The main reason for this is based on the definition of the concept of risk together with volatility in line with the modern portfolio theory by Markowitz in the 1950s. Although volatility and risk are not synonymous terms, they express the same directional relationship with each other. It is known that risk perception is high in an economy with high volatility. The increase in volatility makes investments riskier. This brings great changes in stock prices.

Another feature of volatility is its permanence. The estimation of the volatility in the future depends on the information set obtained in the present. Volatility is considered to be permanent if the return in the current period can greatly affect the variance estimation in future periods (Engle and Patton, 2001, p. 239).

Volatility is associated with the speed of information flow. If information comes in clusters, asset returns or prices may fluctuate as the market adapts perfectly and instantly to the news. Studying the volatility spill can help decipher how information is communicated between assets and markets. Whether the volatility correlates between the markets is important when examining the speed at which the market adapts to new information. Additionally, it is assumed that changes in market volatility are related to the volatility of macroeconomic variables (Hong, 2001, p. 184).

Determining the reasons for volatility in the stock market has been investigated by policymakers and market actors. Policymakers focus on the factors that determine volatility and how these affect the real sector whereas market actors are concerned with how volatility determines pricing in the stock market and its effects on hedging.

While volatility refers to the variability in the returns of financial assets, it is also an important indicator for estimating the returns of these assets. Volatility in the capital markets is the price mobility of any stock or index during the period under consideration. Stock markets are greatly affected by economic, political, and unexpected disasters. For these reasons, investors need to determine stock price volatility and to predict price changes (Kanalıcı Akay and Nargeleçekenler, 2006, p. 6).

Volatility in financial markets is carefully observed by investors and policymakers. High volatility can be considered as high risk, and investment decisions can change. At this point, whether investors are risk-takers or risk-averse shapes their investment decisions. The situation differs for policymakers. According to them, the fluctuation that will occur in the stock markets may affect the real sector, which may affect macroeconomic variables such as inflation, investment expenditures, and growth. Thus, large volatility in financial markets can harm the economy.

Opinions differ on how fluctuations in stock markets affect consumption expenditures. According to one view, the decrease in stock prices increases future uncertainty and decreases consumption and investment expenditures. According to another view, consumption expenditures will not be affected as much as it is thought because the actors in the stock market are in the high-income group (Garner, 1988, p. 4).

In studies investigating the determinants of volatility changes in stock markets, five main factors stand out (Nelson, 1996, p. 3-4):

- Positive serial correlation occurring in volatility; major changes come after major changes. Similarly, minor changes are followed by minor changes. Major movements in the current period may shape volatility expectations in future periods.

- Days on which stock transactions can and cannot be made. Both trading and nontrading days are known to contribute to market volatility. Markets are expected to be more volatile on Mondays compared to the other days of the week.

- Leverage effect. A company with a decreasing stock price needs a higher leverage ratio and therefore increases the volatility in its earnings.

- Recession and financial crises. During economic and financial crises, volatility in stock markets is expected to increase.

- Nominal interest rates. With the rise in nominal interest rates, there is an expectation that market volatility will also increase.

In models used to determine volatility, the features of financial time series should also be included. Therefore, instead of using classical econometric methods that act on the assumption of constant variance in the measurement of volatility, models that allow time-varying variance should be used (Büberkökü and Kızıldere, 2017; Emeç and Özdemir, 2014). It is striking that there are different calculation methods of volatility. The first is the basic or dynamic standard deviation method. Another is the autoregressive conditional heteroskedasticity

(ARCH) method and its many versions. To be able to apply the ARCH method, the error terms must have the property of time-varying variance.

In this study, the daily opening values of the ISE100 Index, which is obtained by considering the days when the Istanbul Stock Market is open for trading, were used. The aim, while covering the period from 02.01.2003 to 30.09.2022, is to determine the best autoregressive conditional variable variance model that models the volatility of the ISE100 Index in Turkey using model selection criteria.

This study consists of four main parts. The first part includes the theoretical foundations of the concept of volatility. The second part examines the empirical studies on stock market volatility in the literature. The third section explains the ARCH/GARCH models used while the volatility of the Istanbul Stock Market series is tested. Finally, the fourth part brings the conclusions and suggestions.

2. Empirical Literature

When analyzed from a macroeconomic perspective, the volatility experienced in stock markets affects many economic areas. Therefore, a great deal of theoretical and empirical research has been done. The empirical estimation and measurement of this volatility are very important for both policymakers and investors. This section considers examples of literature on measuring volatility in stock markets.

Fabozzi, Tunaru, and Wu (2004) investigated volatility in China's Shenzhen and Shanghai stock markets. Using the daily data set between 1.11.1992 and 1.11.2001, it was determined that the explanatory power of the GARCH(1,1) model for the Shenzhen stock market and the TGARCH(1,1) model for the Shanghai stock market were higher.

Goudarzi and Ramanarayanan (2010) determined the volatility of the Indian stock market with ARCH-GARCH models. The BSE500 Index was investigated using the daily data set between 26.07.2000 and 20.01.2009. According to results, the GARCH(1,1) model was determined as the model that best explained the volatility of the stock index.

Uğurlu, Thalassinos, and Muratoğlu (2014) compared the stock market volatility of four European countries and Turkey in their study. Evaluating Bulgaria, Czech Republic, Poland, Hungary, and Turkey, daily data between 08.01.2001 and 20.07.2012 were used and it was determined that GARCH, GJR-GARCH, and EGARCH effects were present in all markets except Bulgaria. It was determined that old news affects volatility in these markets.

Al-Najjar (2016) modeled volatility for the Amman Stock Exchange and identified the impact of volatility on risk and portfolio management. For this purpose, the daily data set covering January 1, 2005 to December 31, 2014 was used. ARCH, GARCH, and EGARCH models were used and it was determined that the GARCH model was the most effective in explaining volatility.

Ali, Suri, Kaur, and Bisht (2022) analyzed volatility in the Indian stock market using a daily data set covering January 1, 2008, to December 2, 2021. GARCH(1,1) and FIGARCH methods were used and the presence of the GARCH effect was observed. It was determined that the effects of shocks on the economy continued for a long time. On the other hand, it was determined that the effect of bad news on stock volatility was greater than that of good news.

Kalaycı (2005) used a monthly data set covering 1990–2003. In this study, in which the sources of the ISE100 Index return volatility were investigated, it was concluded that inflation and money supply variables affected the ISE return volatility, together with the regression model created by estimating the volatility with the GARCH(1,1) method.

Kanalıcı Akay and Nargeleçeken (2006) investigated the volatility effects by considering the closing prices of the ISE National 100 Index covering October 23, 1987, to July 28, 2006. The most suitable model was determined by using ARCH/GARCH models where the GARCH(1,2) model was the most significant and most suitable model. According to the results, despite the increase in index volatility, which was noticeable during crisis periods, the volatility decreased after the uncertainty environment was eliminated.

In Özden's (2008) study, the logarithmic return series of the daily ISE100 Index covering the period between 04.01.2000 and 29.09.2008 was used. In the study, the return series determined to have ARCH effect were tested separately with conditional heteroskedasticity models and the study concluded that the most significant model was TGARCH(1,1).

Atakan (2009), using the daily closing data of ISE100 Index between 03.07.1987 and 18.07.2008, researched the most proper model for the determination of volatility in the Istanbul Stock Market. The results concluded that the volatility of the ISE100 Index had the effect of ARCH and the most appropriate model for estimating the volatility was the GARCH (1,1) model.

In Çabuk, Özmen, and Kökcen (2011), data on the ISE100 national index, Service index, and financial index between 2004–2009 were searched daily. This study aimed to determine the most appropriate model to define volatility and the EGARCH(1,1) model was determined as the model with the highest explanatory power in explaining volatility.

The daily return series of the ISE100 Index between 04.01.1995 and 18.06.2010 was used by Güriş and Saçaklı Saçıldı (2011). It determined the model in which volatility is best explained by using the classical and Bayesian GARCH models. According to the findings, it was concluded that the Bayesian GARCH model gave significant results in the period range that was the subject of the analysis in terms of determining the volatility.

Karabacak, Meçik, and Genç (2014) aimed to determine the most suitable conditional heteroskedasticity model to model volatility by using the closing prices of the daily ISE100 Index between January 3, 2003, and September 11, 2013. The most appropriate model in terms of ISE100 Index volatility was the

TARCH(1,1) model. In line with this model, it has been determined that there are asymmetrical effects on the ISE100 Index return.

In Kuzu (2018), the volatility of the closing values of the daily ISE100 Index was tested across 4.2011–4.2017. The model that best explained the existence of volatility was the TGARCH model, as it gave the most significant results in explaining the existence of volatility.

Taştan and Güngör (2019) used the daily closing data set of the ISE100 Index between January 1, 2001 and January 4, 2019. In the first stage of the study, the long-term component of volatility was estimated using the GARCH-MIDAS method, and in the second stage, macroeconomic indicators affecting the long-term volatility were analyzed. It was concluded that the exchange rate variable was the most important determinant in explaining the volatility of the ISE100 Index. Additionally, the inflation rate was not a significant variable affecting volatility. Finally, it was observed that the increase in the real sector confidence index decreased the index volatility.

In their study, Ay and Gün (2020) estimated volatility modeling using the daily closing data of the ISE Bank Index. In the analysis covering between January 4, 2010, and December 31, 2019, the model that gave the best results in estimating the volatility modeling of the ISE Bank series was TGARCH (0,1,1) when evaluated according to the information criteria. However, when compared according to forecasting performance, the EGARCH (1,1,1) model gave the best results.

Atıcı Ustalar and Şanlısoy (2021) analyzed the impact of the crisis created by the COVID-19 pandemic process on the volatility of the stock markets in Turkey and the G7 countries. The closing prices of the stock market indices of the countries in question were the subject of the research. The EGARCH(1,1) model was used, in which the daily data set was used between March 11, 2020, and January 15, 2021. According to the findings, the increase in the number of daily cases in Turkey, Canada, France, and Japan increased the volatility in the stock market indices.

Güzel and Acar (2021) investigated how stock markets were affected during epidemics. The study, based on the example of the Istanbul Stock Market, tried to determine the appropriate volatility model among ARCH, GARCH, T-GARCH, and EGARCH models by considering the date range 1/2/2009–8/11/2020. According to the results obtained, it was concluded that the EGARCH (1,1) model was more suitable for modeling the BIST100 Index volatility.

Öner and Öner (2023) aimed to determine the most explanatory model that could be used by both investors and researchers in estimating the BIST100 Index return. ARCH, GARCH, EGARCH, and TARCH models were used in which the date range of 04.01.2010 and 28.07.2020 was analyzed. It was determined that the model with the highest explanatory power among the models that revealed the ISE100 Index return volatility was the TARCH model.

This study aims to determine the model that gives the most meaningful results among the models that explain the return volatility of the ISE100 Index. The ISE100 Index shows the performance of the first 100 stocks traded in the Istanbul Stock Market in terms of market and trading volume and is a very important indicator for investors. The course of volatility in the Istanbul Stock Market has been investigated, especially during the period when the country was governed by the same political authority.

3. Econometric Method

3.1. Autoregressive Conditional Heteroskedasticity (ARCH) Model

The ARCH model was first introduced by Engle in 1982. Although the starting point is to try to explain the inflationary environment in England, it has become a method used for many different variables. With this study conducted in 1982, the error term variance changed over time. It was related to the past values, and there was autocorrelation between the error term variances in the UK inflation variable. In light of this information, the ARCH model was developed in line with the argument that the model should be constructed (Engle, 1982, p. 987).

According to traditional time series models, the variance of the error terms will take a constant value. When examined within the framework of these models, in the presence of the heteroskedasticity problem, the estimator of the least squares method continues to have unbiased and consistent features. However, it will result in statistically insignificant results in the estimation of the parameters. Therefore, it is necessary to eliminate the problem of heteroskedasticity or to construct models that allow this change in variance (Songül, 2010, p. 4).

With Engle's (1982) study, a relationship was established between the error term variance and the squares of the error terms belonging to the previous period. Essentially, the constant variance assumption has been abandoned. With the ARCH model, to model the volatility of the time series that is the subject of the evaluation, it is necessary to include an independent variable that can describe this volatility. Modeling volatility by adding an independent variable can be expressed with the following equation (Enders, 2004, p. 112-113):

$$y_{t+1} = \varepsilon_{t+1} x_t \tag{1}$$

While the variable ε_{t+1} in equation (1) represents an error term with σ^2 variance, x_t is an independent variable. If the independent variable is constant in the past periods, it will be determined that the y_t series is in a white noise process with a constant variance. However, if the independent variable takes variable values rather than constants, the variance of the y_{t+1} variable is shown with the following expression (Enders, 2004; Songül, 2010):

$$Var(y_{t+1}|x_t) = x_t^2 \sigma^2 \tag{2}$$

In equation (2), it is concluded that the actual value of the x_t independent variable and the conditional variance of the y_{t+1} variable are related to each other. Under these conditions, there will be a same-way relationship between the value of the variable and the conditional variance value of the y_{t+1} variable. Therefore, defining the x_t variable also allows the volatility of the y_t series to be determined (Enders, 2004, p. 113).

In case of moving away from the constant variance assumption, the conditional variance is defined as an AR(q) process.

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1\hat{\varepsilon}_{t-1}^2 + \alpha_2\hat{\varepsilon}_{t-2}^2 + \cdots + \alpha_q\hat{\varepsilon}_{t-q}^2 + \nu_t \tag{3}$$

According to equation (3), α_1, α_2, …, α_n values being zero means that the variance value is equal to α_0 value. On the other hand, the conditional variance of y_t occurs in line with the autoregressive process discussed in equation (3). Equation (3) also stands out as a general form of the ARCH model (Enders, 2004; Gürsakal, 2009).

When the estimation process of equation (3) is evaluated as AR(q) model together with Lagrangian multipliers test, the existence of ARCH effect is investigated. The ARCH-LM test statistical value is calculated with the formula $LM = (T-q)R^2$ and includes a χ^2 distribution with q degrees of freedom. According to this;

$$\begin{aligned} H_0 &= \alpha_1 = \alpha_2 = \cdots = \alpha_q = 0 \\ H_1 &= \alpha_1 \neq \alpha_2 \neq \cdots \neq \alpha_q \neq 0 \end{aligned} \tag{4}$$

hypotheses are tested. According to the findings, $\mathrm{if} LM_{ARCH} < \chi_q^2$ table, the H_0 hypothesis is rejected and the existence of ARCH effect is accepted in this way (Gürsakal, 2009; Özden, 2008).

Some features of the ARCH model stand out. These are (Nargeleçekenler, 2011; Songül, 2010):

- Conditional variance parameter must be positive
- $\alpha_{0,}$ α_1, α_2, …, α_n parameters must be positive
- It must be "$\alpha_i \geq 0$" with $\alpha_0 > 0$ and I = 1,2,...,p
- If α_1, α_2,…,α_n = 0 then variance = α_0
- Each or sum of α_n's must be less than 1. The stability of the ARCH process is provided by this constraint.

The ARCH model, developed by Engle in 1982, has been the subject of research in many different ways. The ARCH model, which was reconsidered with the studies of Bollerslev (1986), Engle, Lilien, and Robins (1987), Nelson (1991), and Baillie, Bollerslev, and Mikkelsen (1996), was generalized and developed. Among these different models, the GARCH model, which is the most frequently encountered in the literature, was used.

3.2. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

The ARCH model is a conditional heteroskedasticity model based on the assumption that error terms follow an AR process. With the GARCH model developed by Bollerslev in 1986, it is accepted that the error terms follow the ARMA process. With this assumption, the GARCH model was created.

Since ARCH model analyses allow the lag lengths to go back much further, the number of parameters to be estimated increases, and therefore it becomes difficult to fulfill the assumption that the equation parameters are not negative. To eliminate this problem, the GARCH model has been developed. According to the ARCH(q) process, the conditional variance is specified only as a linear function of past sample variances. In the GARCH(p,q) process, lagged conditional variances are also included. In this way, the GARCH model has been applied (Bollerslev, 1986; Songül, 2010).

The most general representation of the GARCH(p,q) model is as follows (Bollerslev, 1986, p. 308-309):

$$\varepsilon_t|\psi_{t-1} \sim N(0, h_t), \tag{5}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} = \alpha_0 + A(L)\varepsilon_t^2 + B(L)h_t \tag{6}$$

In the GARCH model expressed by the equation above, some constraints need to be met. These constraints are $p{\geq}0, q{>}0; \alpha_0{>}0, \alpha_i{\geq}0, i{=}1,\ldots,q,; \beta_i{\geq}0, i{=}1,\ldots,p$. On the other hand, in the case of the GARCH(1,1) model, which is frequently encountered in the literature, it is observed that there is a condition of being $\alpha_1 + \beta_1 < 1$ (Bollerslev, 1986, p. 311).

ARCH and GARCH models are frequently used models in the literature for measuring conditional variance. The importance of these models in the calculation of financial volatility in the literature is discussed in Franses and McAleer (2002) studies. With the GARCH model, it is possible to construct models with fewer coefficients and it is easier to control the constraints specific to these coefficients.

3.3. Data Set and Analysis Results

The daily opening values of the ISE100 Index covering the period between 02.01.2003 and 30.09.2022 were analyzed, taking into account the days when the Istanbul Stock Market was open for trading. The volatility analysis of this series, accessed from the Istanbul Stock Market Data Platform, was carried out using the ARCH-GARCH method. The ISE100 Index variable, the subject of the research, was included in the analysis by taking its natural logarithm.

Stationarity is accepted as the first step of time series analysis. As such, the stationarity research of the series in question was carried out.

Table 1: Results of unit root tests

	ISE100 Index	
	Test Statistics	**5% Critical Value**
ADF unit root test	2.156699	−3.410712
Phillips Perron (PP) unit root test	2.729006	−3.410711

According to both ADF and Phillips Perron (PP) unit root test results, Table 1 shows that the ISE100 Index return series contains a unit root at the 5% significance level. The stationarity level is retested by taking the first difference of the series. It has been determined that the d(ISE100) series, whose first-order difference is taken, is stationary in the direction of ADF and PP tests.

Table 2: Results of the series with first-order difference of unit root tests

	d(ISE100 Index)	
	Test Statistics	**5% Critical Value**
ADF unit root test	–31.63209	–3.410712
PP unit root test	–76.28813	–3.410712

Table 2 shows the stationarity test results of the ISE100 return series with first-order difference. The ISE100 series, whose difference is taken, is stationary at the 5% significance level. It has been determined that the series, whose first difference is taken, becomes stationary.

To define the concept of volatility in the context of the variable we are considering, the ARCH-GARCH model is used and, in this direction, lagged conditional variances are added to the model. As the first step to creating this model, it is necessary to develop the mean equations from ARMA models in line with the structure of the variables that are the subject of the research. In this direction, the significance of the parameters of the ISE100 variable was investigated. Accordingly, ARMA(1,1) model was determined as the most suitable model.

Table 3: ARMA(1,1) Model Forecast Results for ISE100 Return Series

	Coefficients	**Standard Error**	**t Value**	**Probability Value**
Constant	0.000689	0.000259	2.666000	0.0077
AR(1)	–0.957716	0.014829	–64.58506	0.000
MA(1)	0.935821	0.017849	52.42944	0.000
AIC	–5.229536			
SC	–5.224282			
Log. L.	12960.17			

ARCH-LM test was performed to investigate the ARCH effect on the error terms of the ARMA(1,1) model estimated for the ISE100 series we discussed. Table 4 shows the results.

Table 4: ARCH-LM test results for the ARMA(1,1) model

F-statistic: 72.50479		Prob. F(5,4944) 0.0000		
Obs*R-squared: 338.1674		Prob. Chi-Square(5): 0.0000		
Variable	**Coefficient**	**Standard Error**	**t Value**	**Probability Value**
c	0.000179	1.42E–05	12.61495	0.000
RESID^2(-1)	0.155862	0.014171	10.99877	0.000
RESID^2(-2)	0.119801	0.014316	8.368347	0.000
RESID^2(-3)	0.032292	0.014407	2.241362	0.0250
RESID^2(-4)	0.033786	0.014313	2.360432	0.0183
RESID^2(-5)	0.084265	0.014145	5.957301	0.000

In Table 4, the existence of the ARCH effect is tested in line with the ARMA(1,1) model. Accordingly, the null hypothesis that symbolizes the absence of ARCH effect is not accepted. That is, the probability values of the ARCH-LM test results of the ISE100 series, which are the subject of the research, are less than 0.05, indicating that there are five ARCH effects of the series. Accordingly, the ARCH(5) model is established.

Table 5: Test results of ARCH(5) model

Variable	**Coefficient**	**Standard Error**	**z Value**	**Probability Value**
c	0.001230	0.000211	5.821153	0.000
AR(1)	–0.991661	0.004259	–232.8406	0.000
MA(1)	0.986478	0.005746	171.6703	0.000
VARIANCE EQUATION				
C	0.000132	4.57E–06	28.97897	0.000
RESID(-1)^2	0.136075	0.010401	13.08233	0.000
RESID(-2)^2	0.154938	0.015743	9.841503	0.000
RESID(-3)^2	0.110543	0.012796	8.638681	0.000
RESID(-4)^2	0.075162	0.012122	6.200568	0.000
RESID(-5)^2	0.126997	0.007746	16.39545	0.000

Accordingly, the system of equations for the ARCH(5) model is:

$$ISE100_t = 0.001230 - 0.991661 ISE100_{t-1} + 0.986478\varepsilon_{t-1} \quad (7)$$

The variance equation is:

$$h_t = 0.000132 + 0.136075h_{t-1}^2 + 0.154938h_{t-2}^2 + 0.110543h_{t-3}^2 + 0.075162h_{t-4}^2 + 0.126997h_{t-5}^2 \quad (8)$$

The equation of variance (8) where all coefficients take positive values. All coefficients in the equation are expected to take positive values and this condition is also satisfied. The sum of the coefficients in the equation (0.136075 + 0.154938 + 0.110543 + 0.075162 + 0.126997 = 0.603715) is less than 1. A value close to 1 in the sum of the coefficients is considered as high volatility. The value of this coefficient is considered as an average size. Therefore, it can be said that the volatility inertia is at a comparatively low level.

To check the presence of ARCH effect in ARCH(5) model ARCH-LM test is applied. The null hypothesis ignores the ARCH effect, and the alternative hypothesis tests whether there is an ARCH effect. In other words, not accepting the null hypothesis indicates the existence of the ARCH effect. Table 6 shows the 1, 4, 8, and 12 delayed ARCH-LM test results.

Table 6: ARCH–LM test results for the ARCH(5) model

F-statistic Obs*R-squared	1.464754 1.464912	Prob.-F-(1,4951) Prob. Chi-Square (1)	0.2262 0.2262
F-statistic Obs*R-squared	1.160276 4.641441	Prob.-F-(4,4945) Prob. Chi-Square (4)	0.3263 0.3261
F-statistic Obs*R-squared	0.849021 6.795202	Prob. F (8,4937) Prob. Chi-Square (8)	0.5593 0.5589
F-statistic Obs*R-squared	5.052463 60.05080	Prob. F (12,4929) Prob. Chi-Square (12)	0.0000 0.0000

According to the findings obtained from the ARCH-LM test, used to determine the volatility of the ISE100 series, volatility was not detected in the 1,4 and 8 lags, while the presence of volatility in the 12th lag stands out. Since all of the lags discussed do not give a common result that there is no ARCH effect, the GARCH model is used. In this way, it is aimed to determine a model without volatility.

The GARCH model is established to eliminate the ARCH effect and to determine which of the ARCH(5) or GARCH(1,1) models of the ISE100 variable is more appropriate.

Table 7: Test results for the GARCH(1,1) model

Variable	Coefficient	Standard Error	z Value	Probability Value
c	0.001183	0.000202	5.860189	0.0000
AR(1)	–0.991729	0.004464	–222.1645	0.0000
MA(1)	0.984987	0.006318	155.8972	0.0000
VARIANCE EQUATION				
C	1.38E–05	1.18E–06	11.73233	0.0000
RESID(-1)^2	0.121560	0.006650	18.27899	0.0000
GARCH(-1)	0.838315	0.007858	106.6868	0.0000

According to Table 7, the GARCH variable reflects significant results. At this point, the ARCH-LM test is applied to detect the presence of ARCH effect in the GARCH(1,1) model. These test results are listed in Table 8.

Table 8: ARCH–LM test results for the GARCH(1,1) model

F-statistic Obs*R-squared	1.066577 1.066779	Prob.-F-(1,4951) Prob. Chi-Square (1)	0.3018 0.3017
F-statistic Obs*R-squared	0.504787 2.020365	Prob.-F-(4,4945) Prob. Chi-Square (4)	0.7322 0.7320
F-statistic Obs*R-squared	0.831969 6.658904	Prob.-F-(8,4937) Prob. Chi-Square (8)	0.5742 0.5738
F-statistic Obs*R-squared	0.850099 10.20697	Prob.-F-(12,4929) Prob. Chi-Square (12)	0.5983 0.5978

Table 8 shows that there is no ARCH effect in the model. When the GARCH(1,1) model is used, it is concluded that the ARCH effect in the ISE100 variable is eliminated.

It is also possible to determine which of the ARCH(5) and GARCH(1,1) models is more suitable. In this direction, it is necessary to examine the model selection criteria of both models.

Table 9: Model Selection Criteria

MODEL SELECTION CRITERIA			
Criteria	**ARCH(5)**	**GARCH(1,1)**	**Best Choice**
Loglikelihood	13351.02	13403.93	GARCH(1,1)
Akaike	–5.386362	–5.408933	GARCH(1,1)
Schwarz	–5.374539	–5.401051	GARCH(1,1)
Hannan-Quinn	–5.382217	–5.406169	GARCH(1,1)

Table 9 shows the selection criteria for both models. Accordingly, it is observed that the GARCH(1,1) model is more suitable in terms of ISE100 variable. The model that is large when examining loglikelihood values, and models that are large in terms of absolute value are considered suitable when examining Akaike, Schwarz, and Hannan-Quinn values. In this direction, when the ISE100 return series, which is the subject of the study, is analyzed, it has been determined that the GARCH(1,1) model is the more appropriate model.

4. Conclusion and Recommendations

Volatility expresses the fluctuation around the equilibrium value of the variable that is the subject of the research. This concept, which has found many different variables in many different markets such as finance, foreign exchange, money, and crypto, has a rich research area. Volatility in the stock market, which is considered the research area of the study, gains importance due to the global integration of financial markets being affected by the decisions of political authorities and being shaped by the perception of risk and uncertainty. The volatility in the stock markets affects many macroeconomic variables, especially international trade, investment, capital movements, and portfolio diversification of investors. As such, estimation of volatility and analysis of how volatility processes work are extremely important for their widespread economic impact.

To estimate the volatility experienced in the stock markets in Turkey, the daily opening values of the ISE100 Index covering 2003–2022 were used. Regarding the series, to determine the model with the highest explanatory power, the stationarity condition of the series was provided and then the constancy of the variance of the error terms was determined by the ARCH-LM test. The partial and autocorrelation functions of the series, which are made stationary by taking the first difference, are examined and the most suitable ARMA model is determined. The ARCH effect is investigated and it is concluded that the series are volatile. This study tried to determine which ARCH or GARCH model was more suitable. Accordingly, as a result of the analysis made for modeling volatility, it is concluded that the most appropriate model is the GARCH(1,1) model. As a result of the ARCH-LM test applied again to investigate the reliability of the model, it is determined that there is no ARCH effect in the GARCH(1,1) model. It is concluded that the GARCH(1,1) model is a model that eliminates the effect of stock market volatility.

As in many countries in the globalizing world, stock markets and the volatility experienced have critical importance in the Turkish economy. Stock markets are extremely important, and directly affect foreign trade and capital movements and indirectly the foreign exchange markets. At this point, as in other variables, the stable structure of the stock markets contributes to the overall macroeconomic stability. The existence of a stable market gains importance in determining the short and long-term capital movements within the country and in creating a portfolio by determining the investment preferences of the investors. However, stock markets are markets where the reflections of the decisions taken by both political authorities and economic policymakers can be followed very closely.

There is a close relationship between volatility and risk perception. Confidence in economies with high volatility decreases and creates risks for investors. High fragility, especially in developing countries, reduces confidence in the economy, and also affects the risk perception of investors. The high volatility causes this cycle to deepen and therefore the fragility of the markets to increase. Volatility has an importance that affects the decision-making processes of investors. In economies with a fragile structure, such as Turkey, where stock markets are heavily affected by the decisions of political and economic authorities, it is necessary to develop policies that will reduce fluctuations in the markets, and implement these announced policies. Studies aimed at understanding the volatility in the stock markets are also important at this point and will be guiding. However, in line with the findings, the ISE100 Index is more affected by negative news rather than positive news. Koy and Ekim Dertli (2016) interpreted this situation as the presence of a leverage effect. Essentially, the volatility of the return of the ISE100 Index increases during periods of uncertainty or economic crisis. It is observed that volatility clusters are formed during these periods.

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