

FORECASTING OF VOLATILITY IN STOCK EXCHANGE MARKETS BY MS-GARCH APPROACH: AN APPLICATION OF BORSA İSTANBUL

MS-GARCH Yaklařımıyla Menkul Kıymet Piyasalarında Volatilite Tahmini:
Borsa İstanbul Uygulaması

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Abstract

The volatility observed in securities markets has an important influence on the decision making processes of stock market stakeholders. In this study, the volatilities in BIST100 index which represents Borsa Istanbul was analyzed. For this purpose, BIST100 index closing data for the period of 03.01.1988-20.04.2018 was used in the study. The BIST100 index was analyzed by Markov regime switching GARCH (MS-GARCH) with three regimes, standard, high and low volatility regimes. As a result of the triple regime MS-GARCH intensive analysis, the existence of endogenous regimens was determined, in which the regime coefficients considered for the index were statistically significant. When the possibilities of regime transitions are analyzed, it is determined that the probability of continuing the standard volatility regime is 0.62, the probability of transition to low volatility regime is 0.23 and the probability of transition to high volatility regime is 0.145. Moreover, it was determined that the possibilities of regime passage in 5 and 20 days are very close to each other.

Keywords:

Volatility, Financial
Risk, Markov
Switching, BIST

JEL Codes:

C58, E42, G32

Özet

Menkul kıymet piyasalarında gözlemlenen volatilite, borsa paydařlarının karar alma süreçlerini etkileyen önemli bir etkidir. Bu çalışmada Borsa İstanbul'u temsil eden BIST100 endeksinde oluşan volatilite analiz edilmiştir. Bu amaçla, çalışmada, 01.04.1993-20.04.2018 dönemi BIST100 endeksi kapanıř verileri kullanılmıřtır. BIST100 endeksi standart, yüksek ve düşük volatilite rejimleri olmak üzere üç rejime dönüřtürülerek, Markov Rejim Deęiřim GARCH (MS-GARCH) ile analiz edilmiştir. Üçlü rejimli MS-GARCH modeli ile yapılan analiz sonucunda endeks için ele alınan rejim katsayılarının istatistiksel olarak anlamlı olduđu, endekste rejimlerin varlıđı tespit edilmiştir. Rejim geçiřleri olasılıkları incelendiđinde ise birer günlük süreçte standart oynaklık rejiminin sürme olasılıđı 0,62, düşük volatilite rejimine geçiř olasılıđı 0,23 ve yüksek volatilite rejimine geçiř olasılıđının ise 0,145 olduđu belirlenmiştir. Ayrıca 5 ve 20 günlük süreçte rejim geçiřlerinin olasılıklarının birbirine çok yakın olduđu tespit edilmiştir.

Anahtar Kelimeler:

Oynaklık, Finansal
Risk, Markov
Deęiřim, BIST

JEL Kodları:

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1. Introduction

Modeling and predicting volatility in financial markets plays an important role in economic performance and financial stability. In particular, determining conditional volatility is seen as an important tool for setting risk measures (Ardia, 2008). The emergence of volatility models as an important risk assessment tool in financial markets has increased the interest in these models.

The concept of risk that people face in many areas of daily life can be expressed as the difference between expectations and realizations in financial markets. Risk, which has a significant impact on investor decisions, makes an important contribution to investors' alternative among the choices they will make for the future. Investors will try to generate income from their investments by taking the necessary financial measures against the risks that may occur in the future due to their investments in the financial markets and by reducing the costs that may arise. For this reason, it is inevitable to use risk management techniques and tools to measure and control the risks that may arise for the related investments. Increasing the ability of investors to manage risk will increase the appetite for accepting the risks underlying the desire to earn income and for making decisions for the future and this will also contribute to the development of financial markets. At this point, it can be stated that regime switching models and Bayesian prediction techniques are among the current methods in terms of risk assessment. For many risk managers, these models are considered difficult to use due to the difficulty of the prediction procedures included (Satchell and Knight, 2011).

Financial markets, are an event that will affect the market, attitude, new information entry, asymmetric information, legal regulations, macroeconomic effects etc. when faced with a situation, a change in price regimes may cause sudden leaps. In financial markets, increases and decreases in the index or securities price series above the averages can be defined as volatility. Since the existence of volatility is an important risk factor, it causes small investors to move away from the markets, it also causes decrease in transaction volume and speculators to make short term transactions. Determining the conditional volatility process has a key role in the risk management system (McNeil, Frey and Embrechts, 2015). In other words, it is very important for the market stakeholders to be able to predict volatility in advance, to maximize earnings or to keep losses to a minimum. For such reasons, the volatility forecast plays an important role in the financial markets and is of great importance to market stakeholders such as portfolio managers, market makers, investors and speculators. Estimation of volatility in financial markets will enable policy makers to make more effective decisions against potential breaks (Poon and Granger, 2003).

Political, economic, financial risks are seen to be high generally in the developing countries in which Turkey also takes part. These risks and reasons affecting the markets in many developing countries ensure that volatility in financial markets is at high levels. Effective estimation and modeling of these high volatility structures, especially for emerging markets, have been an important consideration. Many variants of these models have been developed since the research on the use of time series models for modeling volatility, the creation of the original ARCH model by Engle (1982) and generalization by Bollerslev (1986). In these developed models, the focus is on catching additional stylized phenomena observed in financial markets such as linear outliers and asymmetries. GARCH type models are among the tools required for risk managers today.

An appropriate risk model should be able to adapt to the characteristics of financial returns. In recent academic studies, many financial assets have shown structural breaks in their volatility dynamics, and ignoring this feature may have a major impact on the precision of volatility estimates (Bauwens, Dufays and Rombouts, 2014; Lamoureux and Lastrapes, 1990).

One way of addressing regime change in the return process can be provided by the Markov Switching GARCH models (MS-GARCH), which allow parameters to change over time according to a variable that cannot be observed separately. These models can quickly adapt to structural changes in unconditional volatility, which leads to improved risk estimates. The parameters of GARCH models are generally assumed to be constant over time. However, the conditional distribution of financial returns differs between stagnation and expansion periods (Marcucci, 2005).

Lamoureux and Lastrapes (1990) stated that their high persistence in volatility may be due to structural changes in the variance process. In line with this view, Cai (1994) and Hamilton and Susmel (1994) independently combine the Markov switching model obtained in Hamilton (1989, 1990) with the ARCH specification and introduce the Markov Regime Switching ARCH model (MS-ARCH). The MS-ARCH model is designed to achieve regime changes in the volatility structure, using the unobservable state variable after the first order Markov Chain process. In other words, using this model, different parameter values will be obtained in different regime structures. Gray (1996), in his study, eliminated some of the problems that the MS-ARCH model contained and derived alternative MS-GARCH models. In the study by Klaassen (2002), Gray (1996) made changes in the model he obtained and stated that the model he obtained made predictions of better volatility.

In this study, it is aimed to evaluate the volatility of the BIST100 index representing Borsa Istanbul within the framework of the regime change approach. For this purpose, the logarithmic returns of the BIST100 index, which was created with the closing data of the period of 01.04.1993-20.04.2018, were analyzed with the MS-GARCH method, and volatility estimates and risk exposure values were obtained. In the second part of the study, there is a literature review, in the third part, data, methods and findings, and in the fourth part, the conclusion and discussion section can be seen.

This article aims to contribute to the literature by analyzing the return volatility of the BIST 100 Index with three-regime MS GARCH models. As a result of the literature research, it is seen that the volatility models for the BIST100 index applied with traditional single regime GARCH type models. However, it should not be ignored that it will exhibit different structures in its volatility in different market periods.

More accurate modeling of risk in financial markets is very important for both decision makers and investors. Unlike other studies in the literature that model BIST100 volatility using traditional GARCH structures, the determination of volatility dynamics for each regime by dividing the index into periods of low, standard and high volatility reveals the original value of this study.

Considering the log-likelihood and parameter significance, it was determined that the three regimes (low, standart and high volatility regimes) MS-GARCH model was suitable for the BIST100 index. Conditional average, ARCH, GARCH and asymmetry parameters were statistically significant. And volatility clusters has been identified for the BIST100 index. When

the regime periods were examined, it was found that the BIST100 index was most likely to be in the standard regime. According to the weekly risk assessments, it was determined that the highest risk occurred on the 5th day during the low, standard and high regime periods.

The study consists of five parts: introduction, literature review, data, method and findings and conclusion and discussion. In the following part of the study, a literature review on the subject is presented first, and then information about the data set and the method applied, and then empirical findings are examined. In the conclusion and discussion part of the study, a general evaluation was made.

2. Literature Review

Stock markets tend to fluctuate constantly, influenced by many positive and negative situations experienced by countries. When these positive or negative shocks experience a serious effect, risk-return performance will be significantly affected in parallel with this situation. Models that take into account regime change behavior are sensitive to repetitive market conditions such as stagnation and expansion, and financial crises or serious market crashes have increased the popularity of these models. Regime switching models are a suitable method for capturing these structural breaks in the financial market and fundamental changes in stock market dynamics.

Turner, Startz and Nelson (1989), Schaller and Norden (1997), Paye and Timmermann (2006), Henkel, Martin and Nardari (2011) found that stock market returns have changed over time and are subject to breaks and parameter instability. Maheu and McCurdy (2000) stated that stock markets display strong regime change behaviors using the Markov switching model, they separated market returns as bull and bear markets. Using the Markov model of change, Schwert (1989) stated that stock volatility was higher during the between the years 1929-1939 Great Depression and other periods of recession.

Stock market volatility is considered as an important indicator of business cycles. Tu (2017) emphasized that modeling taking different regime structures into account gives more realistic results for investors risk analysis. Cai (1994), Hamilton and Susmel (1994) were the first authors to use Markov switching models on financial time series. Excluding the lagged values of the conditional variance in the variance equation allows the probability function to be numerically computable. When using a GARCH type model, since it is a Markov chain with K regimes, the evaluation of probability requires the integration of all KT possible pathways, making the prediction impossible. The authors solved the problem of path dependence by eliminating the effects of regime-specific conditional variances. Gray (1996), Dueker (1997) and Klaassen (2002) focused on the solution of this road dependency problem. Gray (1996) suggested that the conditional distribution of returns is independent of the regime path and integrated of the regimes unobservable path in the GARCH equation with the conditional expectation of past variance. Other authors proposed alternative estimation methods to deal with the road dependency problem. While Francq and Zakoian (2008) use the generalized method of moments (GMM); Bauwens, Preminger and Rombouts (2010) used Bayesian MCMC techniques to predict MS. Augustyniak (2014) estimated the MS-GARCH model using Monte Carlo Expectation Maximization (MCEM) and Monte Carlo Maximum Likelihood (MCML) algorithms.

In another recent study, Ardia, Bluteau, Boudt and Catania (2018) developed an estimation method that allows the GARCH process of each regime to develop independently from other regimes. It can be stated that this approach is advantageous in terms of both eliminating the road dependency problem and facilitating the interpretation of the variance dynamics of each regime. Ardia, Bluteau, Boudt, Catania and Trottier (2019) developed alternatives to this method using the MS-GARCH R Package. Due to this R program developed, possible to predict different types of GARCH type models (eg GARCH and Nelson (1991)). The authors used these models in different risk measures such as value at risk (VaR) and expected shortfall and found that MS-GARCH models gave better results compared to different single-regime GARCH-type models.

In the light of these developments, the applicability of MS-GARCH type models in financial markets have also increased. In parallel with these developments, the viability of MS-GARCH type models in financial markets have increased. Moore and Wang (2007) discussed the stock market volatility of five new countries of the European Union (Czech Republic, Hungary, Poland, Slovenia and Slovakia) in the period 1994-2005. They determined that stock market indices showed high volatility before joining the European Union, and low volatility after joining the Union. Hu and Shin (2008) applied MS-GARCH modeling by using weekly stock market index data of developing countries in East Asia. Marcucci (2005), Wang and Theobald (2008), Visković, Arnerić and Rozga (2014), Abounoori, Elmi and Nademi (2016), Lolea and Vilcu (2018) and Korkpoe and Howard (2019) applied MS-GARCH models on various stock market indexes.

Ardia, Bluteau and Ruede (2019) found that the volatility structure of the bitcoin market shows regime changes. They stated that MS-GARCH models VaR) estimates give more accurate results compared to traditional single regime GARCH models.

In many empirical studies, the volatility structure of Borsa Istanbul (BIST) has been addressed using various GARCH type models, but the fact that the number of volatility estimates taking into account the regime change models has been encouraging for carrying out this study.

Kiliç (2007) analyzes long memory in ISE using the Fractional Integrated GARCH (FIGARCH) model and claims that ISE volatility is a long memory process. Mazibas (2005) compared the fifteen symmetrical and asymmetrical GARCH models in terms of estimation performance for daily, weekly and monthly volatility in ISE. Sevüktekin and Nargeleçekenler (2008) evaluated the performance of alternative models to estimate the volatility of the ISE 100 Index, using daily data in the 1987-2006 period. They stated that the most suitable conditional variance model among the alternative ARCH and GARCH models is GARCH (1,1). Atakan (2009) the GARCH (1,1) model was found to be the most suitable model in estimating the volatility related to the index mentioned. He determined that the volatility of the ISE-100 Index increased during the periods of crisis and uncertainty, and volatility clusters were experienced during these periods. Çağıl and Okur (2010) stated that there is a significant increase in volatility and the impact of the shock in the market will be felt for a longer time. Karabacak, Mecik and Genc (2014) investigated which GARCH type model is more suitable for modeling both the BIST100 index and the volatility of gold returns. They determined that shocks have asymmetrical effects and TGARCH (1,1) model is suitable for BIST 100 index returns. Şahin (2016) used ARCH, GARCH, EGARCH and TGARCH models to compare the volatility of the

BIST100 Index and the BIST Corporate Governance Index. According to the results obtained from the study, volatility clusters were observed in both return volatility, and the BIST100 Index had higher volatility than the BIST Corporate Governance Index. Kuzu (2018) discussed the return volatility of the BIST 100 Index with the ARCH, GARCH, EGARCH and TGARCH models, using the daily closing values for the 2011-2017 period. It has been determined that TGARCH model is the most suitable model for the estimation of BIST100 Index volatility.

Güriş and Saçıldı (2011) modeled the volatilities of the returns of the stocks traded on the ISE comparatively with the help of both classical and Bayesian GARCH models. They found that Bayesian models of GARCH type gave more significant results in modeling volatility structures of their returns compared to the traditional GARCH models. Gürsoy and Balaban (2014) used the GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1) models and solutions of the same models with the Support Vector Machines approach. GARCH models, which are solved with the Support Vector Machines approach, perform better than conventional GARCH models.

Çavdar and Aydın (2017) discussed the volatility of the BIST Corporate Governance Index with GARCH and SW-ARCH models. According the results the SW-ARCH model, which takes into account the regime change structure, is superior in measuring the volatility of the BIST Corporate Governance Index compared to the traditional GARCH models. Kula and Baykut (2017) aimed to determine the volatility structure of the index by using the daily closing values of the BIST Bank Index for the period of 02.01.1997-31.12.2016. It was determined that there is low risk regime persistence in BIST Bank Index and the index does not exhibit stability switching to low risk regime while in high risk regime. In BIST Bank Index, it was determined that volatility persistence was high in both regimes.

3. Data, Method and Findings

Borsa İstanbul, which has a developing financial market, is a high volatility stock market. Regimes considered to exist for volatility were handled in three categories: high regime, standard regime and low regime, and analyzes were carried out using three regime models. The standard regime period is considered as the period when the returns are stable, the high regime period is when the returns are above the standard regime, and the low regime is the period when the returns are below the standard period. In the analysis, the 01.04.1993-20.04.2018 period and BIST100 index closing data were used. The logarithms of the daily returns obtained from the index closing data were included in the analysis, and RStudio and Eviews package programs were used in the analysis.

In this study, which does not require ethics committee permission and legal permission, research and publication ethics have been followed.

The index and return charts of the BIST 100 index are presented in Figure 1. When Figure 1 is analyzed, it is possible to say that the BIST100 index series show an increasing trend and do not provide the stationary assumption sought in the series for time series analysis. Considering the BIST100 Yield graph, it is remarkable that the series are stationary and volatility clusters are experienced in some years. It is seen that these volatility clusters occurred in 1993, 1994, 1999, 2001, 2008 and 2013. It can be stated that this extreme volatility in the indices occurred during the periods of local and global financial crises and political crises. It can

be observed that the index return series to be used for volatility prediction are distributed around zero mean and exhibit a stable structure. This observation was supported by using unit root tests. Results for unit root tests are shown in Table 1.

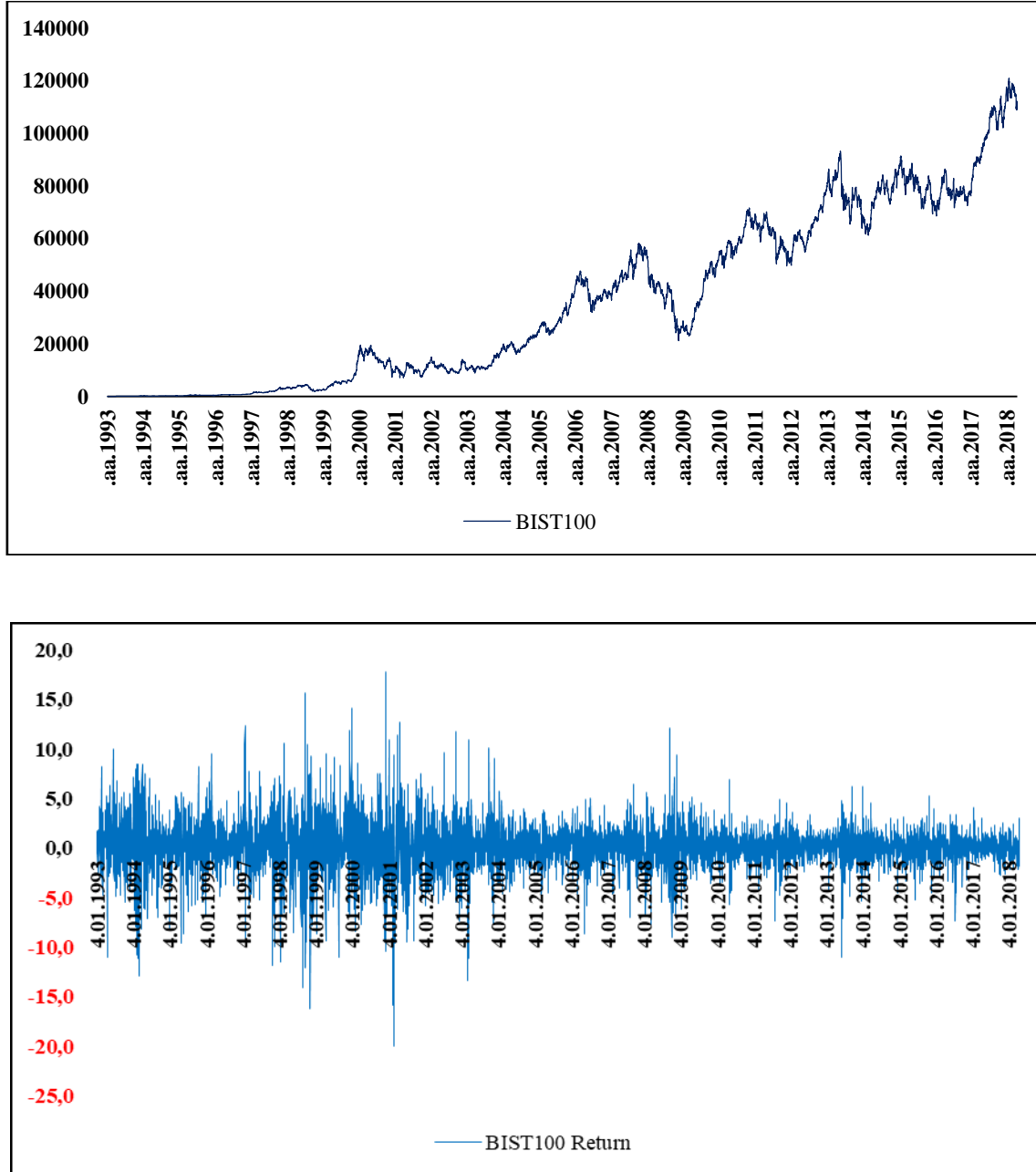


Figure 1. Index and Return Graphs Related to BIST100 Index

According to the descriptive statistics results, the average return on the BIST100 index was positive. While the maximum return calculated in the index is 17.73%, the minimum return is -19.97%, the skewness coefficient is -0.0895 and the kurtosis coefficient is 8.4716. It can be stated that the leptocurtic distribution feature, which is the negative skewness and the more flattened structure, which is frequently seen in the financial series, is seen in the BIST100 return series. The skewness and kurtosis coefficients also show that the BIST100 return series do not

match the normal distribution as a result of Jarque-Bera test statistics. Financial data are generally stated in many studies where they do not provide the normal distribution assumption.

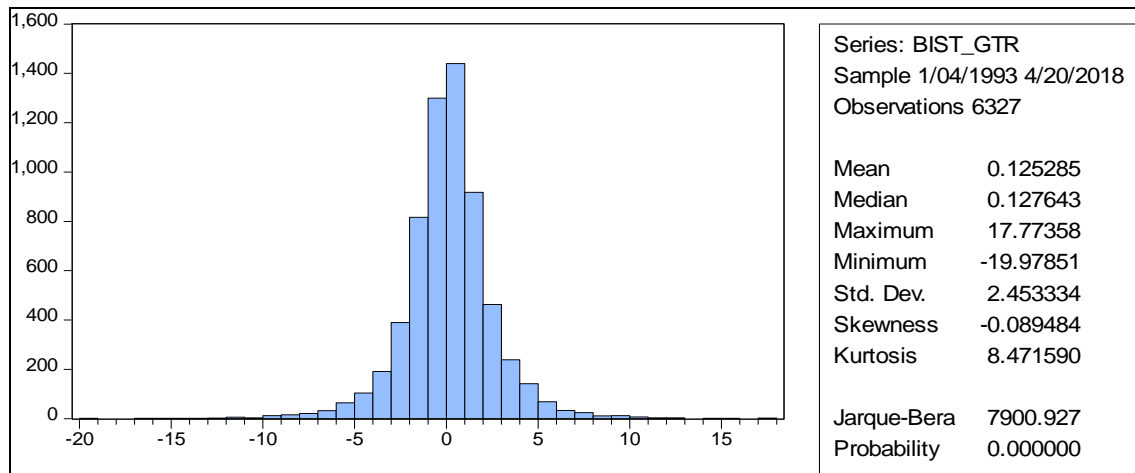


Figure 2. Descriptive Statistics

According to the ADF and PP unit root test results, it was determined that the probability value calculated for BIST100 index return values is less than 0.05, which is considered as the critical value, and the null hypothesis that the series contain the unit root was rejected. The return series were found to be stationary, that is, $I(0)$ according to both ADF and PP test results. It has been determined that the stability condition required for the time series analysis is met. Descriptive statistics for the return series are shown in Figure 2.

Table 1. Unit Root Test Results

BIST 100 Return						
	Test	Difference	Percent	Critical Value	t-Statistics	Probability
Constant	ADF	Level	% 1	-2.565	-75.540	0.000
			% 5	-1.941		
			% 10	-1.617		
	PP	Level	% 1	-2.565	-76.223	0.000
			% 5	-1.941		
			% 10	-1.616		
Trend and Constant	ADF	Level	% 1	-3.960	-75.835	0.000
			% 5	-3.411		
			% 10	-3.127		
	PP	Level	% 1	-3.959	-76.126	0.000
			% 5	-3.411		
			% 10	-3.127		

H_0 : BIST 100 Return has a unit root.

H_1 : BIST 100 Return has not a unit root. (BIST 100 Return Stationary)

In order to perform volatility modeling, it is necessary to determine the presence of non-linear states in the series along with variance and autocorrelation assumption tests. In case of variance, autocorrelation and linear exclusions in the series, ARCH / GARCH type models are needed to perform the volatility prediction. Accordingly, it was first investigated whether the

variance of the error terms related to the BIST100 return series is fixed, i.e. whether it contains heteroscedasticity variance. ARCH-LM test was applied at alternative delays to detect the variance. The values related to the test results are given in Table 2.

When the ARCH-LM test results were examined, it was determined that the probability values calculated for all the delay values considered were below the critical value of 0.05, and the null hypothesis, which stated that the variances of the error terms of the series were homoscedasticity, was rejected. Heteroscedasticity problem was determined in BIST100 return series. Another correlation for the volatility estimation, the autocorrelation assumption, was analyzed by examining the error terms correlograms. The results of the analysis are given in Table 3.

Table 2. ARCH-LM Heteroscedasticity Test Results

BIST100 Return				
Lag	F Statistics	F Statistics Probability	Obs. R²	R² Probability
Lag 1	582.829	0.000	533.732	0.000
Lag 5	204.468	0.000	880.750	0.000
Lag 21	55.6129	0.000	988.289	0.000
Lag 63	22.0930	0.000	1148.415	0.000

H₀: Residuals are homoscedastic
 H₁: Residuals are heteroscedastic

It is determined that the probability values of the Q statistic expressed in Table 3 are smaller than the critical value of 0.05, considering all lagged values. Accordingly, it can be said that the series contain autocorrelation problem. After determining autocorrelation and changing variance presence in BIST100 index return series, it is necessary to determine the presence of nonlinear elements in the series. The presence of nonlinear elements requires the use of GARCH-type models in volatility modeling. The BDS Linearity test proposed by Broock, Scheinkman, Dechert and Le Baron (1996) was used to determine the linearity. Results for the BDS test are shown in Table 4.

Table 3. Correlogram of Error Terms

BIST100 Returns				
	Lag 1	Lag 5	Lag 21	Lag 63
AC	0.049	-0.025	-0.002	0.012
PAC	0.049	-0.027	0.002	0.007
Q-Statistics	15.179	29.068	73.512	154.370
Probability	0.000	0.000	0.000	0.000

When the BDS test results were examined, it was seen that the probability value of the BDS test for the return series was below the critical level of 0.05, and the null hypothesis that the series did not contain non-linear elements was rejected. The necessity of GARCH type models in volatility modeling was revealed with the series containing non-linear elements. In the study, it was analyzed with MS-GARCH models,

which make more effective volatility predictions than volatility models containing non-linear elements.

Table 4. BDS Linearity Test Results

	Dimension	BDS Statistics	Standart	Z-Statistics	Probability
BIST100	2	0.026	0.001	22.019	0.000
	3	0.056	0.001	29.361	0.000
	4	0.077	0.002	34.254	0.000
	5	0.091	0.002	38.791	0.000
	6	0.099	0.002	43.484	0.000

Classical ARCH-GARCH models are based on the assumption that the data set being linear is linear, but observing nonlinear structures especially in long-term data sets causes misleading results with classical models. At this point, the Markov change approach has been proposed as an alternative by Hamilton (1990) in order to determine the statistical definition of the "milestones" of a time series. These models allow a time series that exhibit various volatility structures to frequently switch between regimes through an unobservable regime variable. Changes in regimes can also be estimated by multiple regimes in s_k format. The transition probability matrix of the three-regime and first-order Markov process is equal to the P matrix, which is expressed below:

$$P = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix} \quad (1)$$

Here p_{ij} denotes the probability of a change from the i regime to the j regime. The sum of the possibilities in the whole regime period is equal to 1 ($\sum_{j=1}^3 p_{ij} = 1$). The mean and variance of the s_t regime are expressed as a linear function of s_t as follows.

$$\mu_{s_t} = \mu_1 s_{1t} + \mu_2 s_{2t} + \mu_3 s_{3t} \quad (2)$$

$$\sigma_{s_t}^2 = \sigma_1^2 s_{1t} + \sigma_2^2 s_{2t} + \sigma_3^2 s_{3t} \quad (3)$$

Using the equations, the model can be written as follows.

$$y_t = \mu_1 s_{1t} + \mu_2 s_{2t} + \mu_3 s_{3t} + z_t \quad (4)$$

$$z_t = \sum_{k=1}^2 \varphi_{k,s_t} z_{t-k} + (\sigma_1^2 s_{1t} + \sigma_2^2 s_{2t} + \sigma_3^2 s_{3t})^{1/2} \varepsilon_t \quad (5)$$

If $t = 1, \dots, T$ and s_t depending on the condition, the combined conditional log-likelihood function of y_t can be shown as follows.

$$\log f(y_T, \dots, y_1 | s_T, s_{T-1}, \dots) = -\left(\frac{T}{2}\right) \ln 2\pi - \sum_{t=1}^T \left[\ln \sigma_{s_t} + \frac{v_t^2}{2\sigma_{s_t}^2} \right] \quad (6)$$

Where $v_t = z_t - \varphi_{1,s_t}z_{t-1} + \varphi_{2,s_t}z_{t-2} = \sigma_{s_t}\varepsilon_t$. Since the σ_{s_t} variable cannot be observed and the y_t series are known, the current situation can be obtained by making use of the historical data. Model parameters indicated that the log-likelihood equation proposed by Hamilton (1989) can be estimated using the nonlinear approach as shown below.

$$f(y_T, \dots, y_n) = \prod_{t=n}^T f(y_t | y_{t-1}, y_{t-2}, \dots, y_1) \quad (7)$$

In the study, modeling of the BIST100 return series was carried out by using GARCH type models for each regime period within the framework of the Markov switching structure. Estimation was made by using Markov change EGARCH-SGARCH-EGARCH models, which are tested for each regime. As a result of the model comparisons, the skewed generalized error distribution (sged) was used for the 1st and 2nd regimes, while the skewed student (sstd) distribution was chosen for the 3rd regime. Bollerslev (1987) stated that, since the general feature of time serial data is fat tail, it would be appropriate to prefer Student-t distribution in GARCH models. Ural and Adakale (2009) stated that Student-t distribution shows a symmetrical distribution similar to the normal distribution. The results for the estimated volatility model are presented in Table 5.

Conditional mean parameters ($\alpha_01, \alpha_02, \alpha_03$) were found statistically significant. The ARCH ($\alpha_11, \alpha_12, \alpha_13$) and GARCH (b_1, b_2, b_3) parameters of the MS-GARCH model are statistically significant, which means that there are conditional variance effects. When we look at parameters α_21, α_23 it is seen that the parameters are significant, the effects on volatility are asymmetric. It is possible to say that the negative coefficients have a leverage effect in the stock market, that is, negative shocks that may occur cause more volatility than positive shocks. Mazibas (2005), Kuzu (2018) Karabacak et al. (2014) determined the presence of asymmetric effects for the BIST100 index with single regime models. According to our findings, the presence of an asymmetrical effect was detected in low and high regimes. Student-t and Skewed Student-t distribution parameters were found statistically positive and significant, indicating that the distribution of returns is not normal and skewed to the right. ARCH effect parameters appear to be quite low compared to the GARCH effect parameters. This shows that when the regime changes from a low volatility to a high volatility period, the ARCH parameter decreases and the GARCH parameter increases. It can be stated that the previous volatility values were a more important factor for BIST100 returns during the high volatility periods. In the three main regimes in which the BIST 100 yields are separated, the probability of acting under the standard regime is 79.69%, the probability of continuing under the low regime is 17.43%, and the probability of acting under the high regime is 2.87%. According to this result, volatility analysis with the MS-GARCH method in order to make accurate and reliable decisions will guide the individual or institutional investors in determining what they have to do correctly in their evaluations on the BIST100 index. Similarly, Satoyoshi (2012) and Škrinjarić and Šego (2016) stated that the in-sample and non-sample period volatility estimates of MS-GARCH models in Japan and Croatia stock markets are a good guide for investors.

Table 5. Model Estimation Results

	Parameter	Std. Error	t-Statistics	Probability	
Regime 1					
	α_{01}	0.004	0.003	1.323	0.092
	α_{11}	0.090	0.017	5.239	0.000
	α_{21}	-0.034	0.010	-3.383	0.000
	b_1	0.991	0.002	4.050	0.000
	q_1	1.747	0.088	1.985	0.000
	φ_1	0.983	0.026	3.836	0.000
Regime 2					
	α_{02}	0.135	0.082	1.628	0.051
	α_{12}	0.024	0.027	9.847	0.162
	b_2	0.970	0.003	3.925	0.000
	q_2	1.401	0.122	1.150	0.000
	φ_2	0.780	0.043	1.800	0.000
Regime 3					
	α_{03}	1.227	0.639	1.919	0.027
	α_{13}	0.707	0.189	3.743	0.000
	α_{23}	-0.272	0.108	-2.519	0.000
	b_3	0.648	0.180	3.602	0.000
	q_3	96.534	0.004	2.778	0.000
	φ_3	1.897	0.523	3.627	0.000
Transition Probabilities					
	p_{11}	0.971	0.083	1.166	0.000
	p_{12}	0.029	0.000	1.116	0.000
	p_{21}	0.131	0.010	1.310	0.000
	p_{22}	0.854	0.051	1.660	0.000
	p_{31}	0.000	0.000	6.000	0.499
	p_{32}	0.094	0.007	1.329	0.000
Possibility to Stay in the Same Regime					
	Low	Standart	High		
	(0.174)	(0.797)	(0.029)		
Model Criteria					
	Log-Lik.	-13328.950			
	AIC	26703.910			
	BIC	26859.220			

Conditional variances in volatility models are estimated by maximizing the likelihood function calculated as logarithmic components of their estimated errors. Conditional volatilities obtained as a result of model prediction are shown in Figure 3.

Figure 3 shows the dates with the highest changes in BIST100 returns for the working period of 4.1.1993-20.04.2018. According to the figure conditional variance, the April 5, 1994 extraordinary stabilization program, the political instability in 1995 and the early December 24 elections, the 1998 elections, the government's confidence on January 16, 1999, the crises of November 2000 and February 2001, the financial global crisis that emerged at the end of 2008 and June 12 has the highest values. It is seen that the periods corresponding to the realization of the 2011 elections are reflected on the chart.

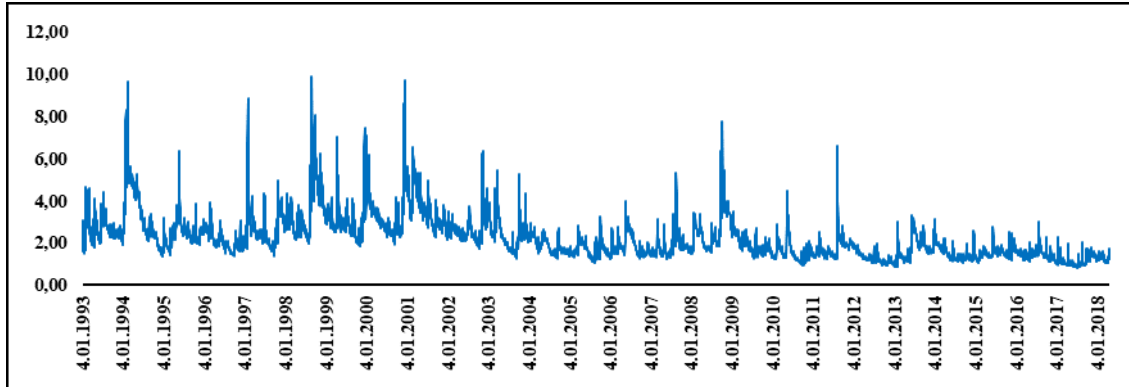


Figure 3. Conditional Volatilities

Transition possibilities between volatility regimes in Table 6, Table 7 and Table 8 are presented for periods of 1, 5 and 20 days, respectively. When Table 6 is examined, it is determined that the regression 1, which represents the standard volatility regime in one day, has a probability of driving 0.997, the probability of transition from regime 1 to a low volatility regime is 0.029 and the probability of transition from regime 1 to a high volatility regime is 0.000. The probability of staying in regime 2 representing the low regime was 0.854, the probability of transition from regime 2 to regime 1 was 0.131, and the probability of transition from regime 2 to regime 3 was 0.015. It is determined that the probability of staying in regime 3, which represents a high volatility regime, is 0.906, the probability of transition from regime 3 to regime 1 is 0.000, and the probability of transition from regime 3 to regime 2 is 0.094.

Table 6. One-Day Regime Transition Probability Estimates

	Regime 1	Regime 2	Regime 3
Regime 1	0.971	0.029	0.000
Regime 2	0.131	0.854	0.015
Regime 3	0.000	0.094	0.906

Table 7. Five-Day Regime Transition Probability Forecasts

	Regime 1	Regime 2	Regime 3
Regime 1	0.895	0.101	0.003
Regime 2	0.463	0.490	0.047
Regime 3	0.093	0.285	0.622

Table 8. Twenty-Day Regime Transition Probability Estimates

	Regime 1	Regime 2	Regime 3
Regime 1	0.813	0.167	0.021
Regime 2	0.761	0.196	0.043
Regime 3	0.571	0.261	0.168

According to Table 7, considering the five-day regime change possibilities, the probability of staying in Regime 1, which represents the standard volatility regime, was 0.895. The probability of transition to Regime 2, which represents a period of less than Regime 1, is 0.101, and the probability of transition to Regime 3, which represents a period of high volatility

from Regime1, is determined as 0.003. The probability of staying in regime 2 representing the low regime was 0.490, the probability of transition from regime 2 to regime 1 was 0.446, and the probability of transition from regime 2 to regime 3 was 0.622. It is determined that the probability of staying in regime 3, which is a high regime, is 0.622, the probability of transition from regime 3 to regime 1 is 0.093, and the probability of transition to regime 2 is 0.285.

When Table 8 is analyzed, it is determined that the regression 1, which represents the standard volatility regime in the twenty-day period, is 0.813, the probability of transition from regime 1 to the low regime is 0.167 and the probability of transition from regime 1 to the high regime is 0.021. The probability of staying in regime 2, which represents the low regime, was determined as 0.195, the probability of transition from regime 2 to regime 1 was 0.761, and the probability of transition from regime 2 to regime 3 was 0.0423. The probability of staying in regime 3, which is a high regime, is 0.168, the probability of transition from regime 3 to regime 1 is 0.571, and the probability of transition from regime 3 to regime 2 is 0.261.

Table 9. VaR Values Based on Regimes

Days	Low Regime	Standart Regime	High Regime
1	-2.021	-4.326	-4.796
2	-1.988	-4.302	-5.804
3	-1.976	-4.485	-6.660
4	-2.007	-4.384	-7.233
5	-2.035	-4.486	-7.640

Considering the probability of acting in regimes, it can be stated that the continuity of the regime is the most probable period in a one-day period, in the twenty-day period. It can be stated that the volatility has decreased partially and the possibility of transition from regime 2 and regime 3 to the standard regime 1 is high.

The five-day VaR results of the regimes for the BIST 100 returns are presented in Table 9. When Table 8, which shows VaR values based on regimes, is analyzed, it is determined that the highest risk of harm in the low, standard and high regime will be at the 5th day and 2.035%, 4.486% and 7.640% respectively.

VaR values of our three regime MS-GARCH model that we prepared in accordance with the purpose of the study are given in Table 10. When Table 10 is examined, if the model is evaluated as a whole, the probability of damaging statistically at the level of 1% and 5% increases to the highest level on the 5th day as in regimes. On the 5th day, the probability of loss at 1% significance level was 4.408% and at 5% significance level it was 2.408%.

Table 10. VaR Values of the Model

Days	% 1	% 5
1	-3.984	-2.319
2	-4.094	-2.269
3	-4.396	-2.398
4	-4.363	-2.328
5	-4.408	-2.408

4. Conclusion and Discussion

In the study aiming to determine the volatility structure of the BIST100 Index with the MS-GARCH model, BIST100 index closing data for the period of 01.04.1993-20.04.2018 was used. Detection of regimes presence was analyzed by three regime MS-GARCH model. The basic assumption of analyzing with time series is that the series are stationary. For this reason, BIST100 index logarithmic returns were primarily tested with Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) unit root tests and the series were found to be stationary at the level. In addition, the Student-t and Skewed Student-t distribution parameters were found statistically positive and significant, indicating that the distribution of returns is not normal and skewed to the right. The yield (Q) and checkered returns (Q2) of the Ljung-Box statistics were found to be significant, indicating that the BIST 100 index returns show a high degree of volatility clustering behavior.

The three-regime MS-GARCH model created was estimated by four different models. In the model estimations, it is determined that MS-EGARCH-SGARCH-EGARCH (S-Student) model gives the best results. As a result of the analysis, conditional average parameters ($\alpha_{01}, \alpha_{02}, \alpha_{03}$) were found statistically significant. ARCH ($\alpha_{11}, \alpha_{12}, \alpha_{13}$), GARCH (b_1, b_2, b_3) and asymmetry (α_{21}, α_{23}) parameters in the MS-GARCH model were found to be statistically significant, indicating that they had conditional variance effects. It is seen that ARCH effect parameters are quite low compared to GARCH effect parameters. This shows that when the regime passes from a low volatility to a high volatility period, the ARCH parameter decreases and the GARCH parameter increases. This shows that the previous volatility values are a more important factor for BIST100 returns during high volatility periods.

In addition, when the probability of the transitions between the regimes is analyzed, it is determined that the probability of the standard regime period to be realized within one day period is 0.970, the probability of transition from the standard regime to the low volatility regime is 0.029 and the probability of transition from the regime to the high volatility regime is 0.000. When looked at the five-day regime change possibilities it can be seen that the probability of staying in the standard volatility regime is 0.895, the probability of transition from the standard regime to the low period is 0.101, and the probability of transition from the standard regime to the high volatility period is 0.003. When the series are examined in 20-day periods, it is determined that the probability of staying in the standard regime is 0.812, the probability of transition from the standard regime to the low regime is 0.160 and the probability of transition from the standard regime to the high regime is 0.020.

As a result, it was determined that the BIST 100 index representing Borsa Istanbul has standard, high and low volatility regimes. In the securities markets, it is an important factor that speculators, who are an important actor besides investors, can accurately predict the volatility that may occur in order to reveal their future expectations. It is important to be able to estimate the volatility accurately and to estimate the transition possibilities between regimes, to keep the gains maximized and losses to a minimum. For this reason, it will be appropriate for Borsa İstanbul stakeholders and especially institutional and individual investors to make volatility analysis considering the three-regime MS-GARCH model to make the right investment decisions. MS-GARCH model takes the regime transition possibilities determined in the study into account and making investment decisions according to the expectations that are appropriate for the risk levels of the investors. Attracting small investors to the markets, increasing the

transaction volume, attracting long-term investments, increasing the market depth and creating a reliable and low-risk investment environment can be achieved by reducing volatility. In order to achieve this situation, it will be effective to expand the environment of trust and transparency to the market. It will also be effective to raise awareness of social savings, and to carry out studies to ensure that funds are transferred to capital markets.

Researchers Contribution Rate Statement

The authors declare that they have contributed equally to the article.

Conflict of Interest Statement

There is no potential conflict of interest in this study.

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