Volatility of BIST 100 Returns After 2020, Calendar Anomalies and COVID-19 Effect

Ali Çelik*

Abstract

Market actors define the volatility in financial markets as a measure of risk. This study aims to investigate the volatility movements in the return series calculated on the closing values of the BIST 100 index between 01.Jan.2020-11.Feb.2021. In addition, the days of the week anomaly, the dates of public holiday, and COVID-19 pandemic effect were used as dummy variable in the econometric model. The findings showed that the EGARCH (3,3) model is to be the best performing model. Accordingly, Friday's anomaly, Public Holidays, and the COVID-19 pandemic create negative shocks on the volatility movements of the return series, increase the volatility movements, and consequently, asymmetric and leverage effect emerged.

Keywords: Volatility of BIST 100 returns, EGARCH, Calendar anomalies, COVID-19

JEL Classification: G1, G11, G17

Öz - 2020 Sonrası BIST 100 Getiri Volatilitesi, Takvim Anomalileri ve COVID-19 Etkisi

Volatilite, piyasa aktörleri tarafından riskin ölçütü olarak tanımlanır. Çalışmanınn amacı 01.01.2020 ve 11.02.2021 tarihleri arasında BIST 100 kapanış değerleri üzerinden hesaplanan getiri serisinin volatilite düzeyini ARCH-GARCH tipi modeller ile test etmektir. Ayrıca söz konusu modellerde takvim anomalileri ve KOVİD-19'un volatiliteye etkisi sınanacaktır. Çalışmanın sonucunda, EGARCH (3,3) modelinin en iyi performansı sergileyen model olduğu tespit edilmektedir. Buna göre, Cuma günü anomalisinin, Resmi Tatillerin ve COVID-19 pandemisinin getiri serisinin volatilite hareketleri üzerinde negatif şoklar yarattığı, volatilite hareketlerini arttırdığı, netice itibariyle asimetrik ve kaldıraç etkisi yarattığı sonucuna ulaşılmaktadır.

Anahtar Kelimeler: BIST 100 Getiri volatilitesi, EGARCH, Takvim anomalileri, COVID-19

JEL Sınıflandırması: G1, G11, G17

* Istanbul Gelisim University, Department of International Trade and Finance - E-mail: alcelik@gelisim.edu.tr - ORCID ID: https://orcid.org/0000-0003-3794-7786

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1. Introduction

Globally, information plays a crucial role in the financial market. Quickness in obtaining complete and reliable information depends on the development of the economy. However, in the current circumstance, info is not shared equally between the parties, which reduces the economy's effectiveness, especially for financial markets. The fact that information is not evenly has revealed the concept of asymmetric knowledge. Mishkin (1996, 1998) suggests that asymmetric information will cause adverse selection and moral hazard in financial markets. Developments in financial markets affect not only themselves but also, significantly, the overall economy. Following whether it is financial or real, the well functioning of the market is of great importance for a stable economic system. Though, for developing countries, ensuring and maintaining market stability is not always possible due to the financial markets of those countries are characterized by high fragility and a risky and uncertain environment (Mishkin, 2004). With this regard, it is shown that testing volatility in purchasing financial assets process, especially in financial markets, plays a key role in access to market information and predictability.

In finance theory, there is a direct relationship between risk and volatility. The variance of the probability distribution of financial asset prices or returns is adopted to determine risk premium and volatility. Therefore, the variance distribution is used to measure the financial market's risk (Mazibaş, 2005). In econometrics, conditional heteroscedasticity models are applied to determine an effective and consistent estimation. Symmetric conditional heteroscedasticity (ARCH, GARCH), and asymmetric conditional heteroscedasticity (EGARCH, TGARCH) models generate a solution to measure the series having heteroscedasticity issues. In addition, these models involve distinct differences. For instance, symmetric conditional heteroscedasticity models respond similarly to negative and positive shocks. On the other hand, the asymmetric conditional heteroscedasticity model gives different responses to negative and positive shocks. For this reason, it is assumed that asymmetric conditional heteroscedasticity models provide results that are more coherent and realistic than symmetric conditional heteroscedasticity. Besides, it is presumed that these models (ARCH-GARCH family models) that eliminate the problem of heteroscedasticity have the best performance (Engle, 1982; Engle and Bollerslev, 1986; Bollerslev, 1986; St, 1998; Zakoian, 1994).

This study aims to examine the volatility movements of the BIST-100 return series. The return series was calculated by taking the BIST-100 daily closing values over the time span 01.Jan.2020 -11.Feb.2021. Additionally, the days of the week anomaly, the dates of public holiday, and COVID-19 pandemic effect were used as dummy variable in the econometric model. The study continues with a literature review after the introduction section. Several relevant works of literature are discussed in section 2 while presenting the econometric methodology in section 3. In section 4, empirical analysis is made with ARCH-GARCH models. The last section 5, is reserved for the conclusion and policy proposal of the study.

2. Literature Review

The creation and collapse of the Bretton Woods system have characterized two critical periods in international capital movements. As the disintegration of the Bretton Woods system created the conditions for the transition to a flexible exchange rate regime, the world economy entered a new era. Moreover, the process of liberalization of capital movements began gradually. It is clear that these developments allow the emergence of financialization phenomenon. With the phenomenon of financialization, short-term capital movements are hypersensitive to risks due to their speculative nature, become a crucial problem area, especially in developing countries with a relatively high-risk premium. In addition, it is recognized that incidental or inherited problems in countries' economies, or an environment of uncertainty and instability, intensively affect volatility in financial markets. Market actors define volatility in financial markets as a measure of risk. From this point of view, determining the risk and volatility situation significantly affects the decisions of market actors in trading financial assets or liability held for trading. Conditional heteroscedasticity models, on the other hand, meet this need in financial markets. A summary of the literature of important studies on this topic is collected as follows.

Özden (2008) calculated daily return values using the IMKB[1] (The Istanbul Stock Exchange)-100 closing index throughout 04.Jan.2000-20.Sep.2008. In the analysis, the volatility of the series was tested with GARCH, EGARCH, and TGARCH models. Accordingly, TGARCH (1,1) had been suggested as the best model. Çağıl and Okur (2010) examined the volatility of IMKB-100, IMKB-30, and IMKB National-All indices using GARCH models for the daily return data over the period of 2004-2010. According to the test result, volatility was quite high and resistant, especially between 2007 and 2010. Güris ve Sacaklı (2011) calculated the return series using the IMKB-100 daily closing index over the 1995-2010 period by testing the volatility level with conditional heteroscedasticity models to determine the model, performed the best among these models. Accordingly, the GARCH model showed the best

1 Its name, which was Istanbul Stock Exchange (IMKB), was changed to ''Borsa Istanbul (BIST)''on April 5, 2013.

description of the series. Chand et al. (2012) examined the daily closing values of Pakistan Muslim Commercial Bank (MCB) and the volatility of financial asset return using conditional heteroscedasticity models. GARCH (1,1) revealed the best performing model. Mgbame and Ikhatua (2013) were examined the stock market index volatility of the 100 largest companies in Nigeria between 2000-2010 by GARCH (1,1), EGARCH (1,1), TGARCH (1,1) models and concluded that the Nigeria stock market index has high volatility. Lama et al. (2015) examined volatility in table oil and international cotton price index with ARIMA, GARCH, and EGARCH models during April 1982-March 2012. Among these models, the EGARCH model presented the most effective result. Accordingly, the asymmetric conditional heteroscedasticity models produced consistent results describing volatility in the international cotton price index. Maqsood et al. (2017) examined the volatility in daily return of the Kenyan Stock Exchange (NSE) during the period's March 2013-February 2016 by using symmetric and asymmetric GARCH models, and the analysis showed that the volatility process is highly resilient while the risk premium in the NSE return series is high. Kuzu (2018) calculated the volatility values of the related series by using conditional heteroscedasticity models (ARCH, GARCH, EGARCH, TGARCH) with daily closing value data over 2011-2017 of the BIST (The Istanbul Stock Exchange) 100 index. Along with, conditional heteroscedasticity models that perform the best are tested, and the TGARCH model came to the forefront. Komşuoğlu (2019) used daily return data over 31.Dec.2009-31.Dec.2018 to analyze the validity of the effective market hypothesis by using ARMA, ARCH, and GARCH models. Accordingly, the findings showed the validity of the random walk, and the efficient market hypothesis has been rejected. Bayçelebi and Ertugrul (2020) analyzed the volatility of the BIST index with the help of conditional heteroscedasticity models by using daily closing value during 2010-2016. In this context, the ARCH effect disappeared, and volatility movements could be detected within the framework of GARCH(1,1).

Studies testing the volatility of economic variables using conditional heteroscedasticity models are presented in the literature. Detecting the presence of volatility in financial markets straight affects the risk perception of investors or market makers. Besides, it directs the decisions of suppliers and purchasers in the loanable funds or financial market. Another important factor affecting volatility movements is the days of the week anomaly (Alberg et al., 2008; Kohli, 2012; Osarumwense, 2016). Studies testing conditional heteroscedasticity models using the days of the week anomaly made significant contributions to this field (Krezolek, 2018; Obalade and Muzindutsi, 2019; Adaramola and Adekanmbi, 2020).

3. Methodology

As is known, many economic variables do not act in a straight line. On the contrary, they have a continuous fluctuation course. This movement is characterized as the cycle of conjuncture. The pressure of a number of factors inside and outside the economy affects macroeconomic magnitudes. These factors cause several fluctuations in the economy. From the econometrics window, such fluctuations also alter the variances of the series. Therefore, one of the assumptions made for error terms, the condition that error terms have homoskedasticity, will disappear, and the situation of heteroscedasticity will occur. In econometrics, tests were developed to consider the conditional heteroscedasticity to be able to effectively and consistently forecast such series. These include two categories; symmetric and asymmetric conditional heteroscedasticity. In the first study, two sub-models of symmetric conditional heteroscedasticity, the autoregressive conditional heteroscedasticity (ARCH) and the generalized autoregressive conditional heteroscedasticity (GARCH) model, were used. The ARCH model developed by Engle (1982) is as follows:

$$e_t = v_t\sqrt{h_t} \quad (1)$$

$$h_t = \alpha_0 + \alpha_1 e_{t-1}^2 + \alpha_2 e_{t-2}^2 + \cdots + \alpha_p e_{t-p}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 \ , \qquad e_t = Y_t - X_t b \quad (2)$$

The h_t symbol refers to the conditional variance of the ARCH model; v_t has a white noise process and is independent of h_t; the p s symbol refers to the degree of the ARCH process, and the α symbol denotes an unknown parameter vector. The e_t symbol denotes an error term. While $X_t b$ is the conditional average of the Y_t series, h_t are known conditional variances. Moreover, the series in question has a normal distribution. As an alternative to the shortcomings of the ARCH model, the generalized autoregressive conditional heteroscedasticity (GARCH) model was established by Bollerslev (1986) as a model that can give a more appropriate lag length and reveal better the effects of the past. The equation of the GARCH model is as follows:

$$e_t/\psi_{t-1} \sim N(0, h_t), \quad (3)$$

$$e_t = Y_t - X_t b \quad (4)$$

$$e_t = v_t\sqrt{h_t} \ ; \quad \sigma_t^{\,2} = 1 \quad (5)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{i=1}^{q} \beta_i h_{t-j} \quad , \qquad (6)$$

In conditional variance (h_t), is affected by the past period of conditional variance with the error term. The GARCH (p,q) model is successful in determining the volatility of financial time series (Brooks, 2008: 394). ARCH and GARCH models homogeneously consider the effect of positive or negative shocks on volatility (Engle and Bollersley, 1986). Hitherto, what is meant by its symmetrical state is to assume that the effects of positive and negative shocks are similar. However, in practice, negative shocks or news affect volatility more compared to positive shocks or news. Black (1976) described this situation as the leverage effect. According to the leverage effect, often encountered in financial markets, negative news increases the risk premium more than positive news. The GARCH model was distinguished by its successful stance in the financial time series. Nevertheless, this model uniformly takes the effect of these shocks on volatility has also been exposed as its weakness. Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH) models were developed in the form of asymmetric conditional heteroscedasticity models established to overcome the shortcomings of symmetric conditional heteroscedasticity models and obtain results closer to reality. Nelson (1991) first introduced the exponential GARCH (EGARCH) model. EGARCH model is the unrestricted version of ARMA (p, q) models. The equation of the EGARCH model is as follows:

$$lnh_t = \alpha_0 + \sum_{i=1}^{n} \beta_i lnh_{t-i} + \sum_{i=1}^{n} \theta \frac{e_{t-i}}{\sqrt{h_{t-i}}} + \sum_{i=1}^{n} \gamma \left| \frac{e_{t-i}}{\sqrt{h_{t-i}}} \right| \qquad (7)$$

In Eq. (7) h_t is the conditional heteroscedasticity, the lagged value ofh_t, $\frac{e_{t-1}}{\sqrt{h_{t-1}}}$ and $\left|\frac{e_{t-1}}{\sqrt{h_{t-1}}}\right|$ parameters are used to explain the behaviors of the conditional variance. Unlike the standard GARCH model, the presence of asymmetric volatility in the EGARCH (p, q) model is determined by the θ parameter when it is significantly different from 0 (zero). Here, $\theta \neq 0$ indicates that there is an asymmetric effect and if θ <0, there is a leverage effect, that is, negative shocks of the same magnitude have a greater effect on volatility than positive shocks (Nelson, 1991).

Another of the asymmetric conditional heteroscedasticity models is the threshold generalized autoregressive conditional heteroscedasticity (TGARCH) model (Zakoian, 1994). The distinguishing feature of the TGARCH model is that it takes into account the asymmetry in volatility. In this model, the effects of positive and negative shocks on volatility differ from each other. The conditional variance of the TGARCH model can be expressed as follows.

$$h_t = w + \sum_{i=1}^{p} \alpha_i e_{t-i}^2 + \sum_{j=1}^{q} \beta_i h_{t-j} + \sum_{k=1}^{r} \gamma_k e_{t-k}^2 D_{t-k} \quad (8)$$

In Eq. (8) γ_k is the parameter that describes the leverage effect. Indeed, this parameter is nonzero ($\gamma_k \neq 0$) introduces the existence of the asymmetric effect. If the parameter γ_k is statistically significant and higher than zero ($\gamma_k > 0$), the leverage effect will be mentioned. In other words, negative shocks affect volatility (conditional variance) more than positive shocks. After examining the theoretical background of conditional heteroscedasticity models, the theoretical explanation of the calendar anomalies approaches is included in the analysis (Zakoian, 1994).

Calendar anomalies are the fact that the effect of a particular period unusually affects price movements. According to this approach, it is possible to explain the sequence of outward price movements in financial markets with the help of calendar anomalies (Yavuz, Güriş, and Kıran: 2008). There are several types of calendar anomalies. In this analysis, the effects of Monday, Tuesday, Thursday and Friday as the days of the week anomaly and public holiday as the holiday effect anomaly were considered. The average equation of which the days of the week is denoted as follows:

$$r_t = \mu_0 + \mu_1 r_{t-1} + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_{PH} + \beta_6 D_C + \varepsilon_t \quad (9)$$

In Eq. 9 includes the days of the week, the days of public holiday, and the COVID-19 effect. Here, where the r_t refers to daily return, represents the dummy variables for Monday, Tuesday, Thursday, and Friday[2], respectively (Çil, 2018). Furthermore, D_{PH} and D_C are the dummy variables that describe the dates of public holiday and the date of the first death in Turkey due to the COVID-19, respectively. Public holidays have an impact on the volatility movements in financial markets. In this context, the ''public holiday'' day anomaly were used as dummy variable. Therefore, in creating dummy variables and periods process in which anomalies occur in the data set takes the value 1 (one), while the others take the value 0 (zero). World-scale phenomena such as a pandemic, war, and major economic crises similarly affect both the real

2 To avoid the dummy variable trap, using m-1 explanatory dummy variables is sufficient. Hence, four days of the week except for the weekend analyzed the day anomalies.

and the financial sector indicators. In this respect, the COVID-19 pandemic effect was used as dummy variable. To measure the volatility of the series, the days of the week, the date of public holiday, and the COVID-19 anomaly were demonstrated in the conditional heteroscedasticity equations.

4. Empirical Analysis

The study examines the volatility movements of the BIST-100 return series. The return series was calculated by taking the BIST-100 daily closing values over the time span 01.Jan.2020-11.Feb.2021. The formula below is used in calculating the return series:

$$\text{Return Series} = \ln\left(\frac{BIST100_t}{BIST100_{t-1}}\right) \quad (10)$$

In Equ.10 $BIST100_t$ is the index closing price on day t, $BIST100_{t-1}$ is the index closing price on day t-1. The data is compiled from the Central Bank of the Republic of Turkey database and estimated using the EViews-10 econometric package program. The ARCH and GARCH models apply with stationary time series. For this purpose, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are conducted to analyze whether the parameters contained a Unit Root at the first stage of the analysis. Following these tests, the appropriate ARMA model is estimated. Using the Breusch-Godfrey Serial Correlation LM Test, investigated whether there is an autocorrelation problem. After determining the fundamental characteristic of the series, it is necessary to test the existence of the ARCH effect in the series to apply the ARCH-GARCH family models to the series. The primary logic of the test is to reveal the situation where the current error term and recent error terms are related to each other, which is seen especially in the financial return series and causes the estimation efficiency to decrease if they are not taken into account. In the last stage of the analysis, the series was investigated by conditional heteroscedasticity methods, and calendar anomalies were included in the model.

Figure 1: BIST 100 Return Series

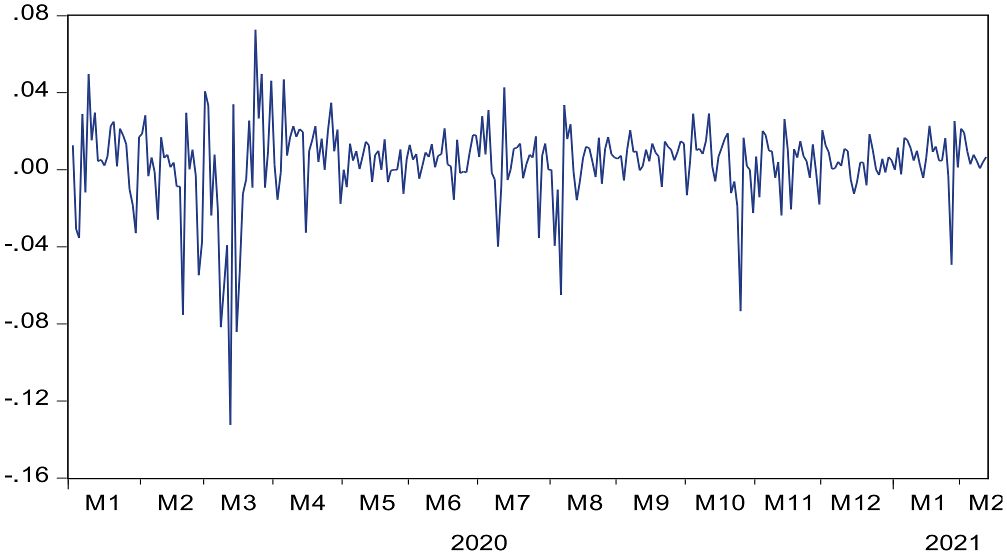


Figure 1 illustrates series fluctuates around a certain environment and therefore carries a stationary property. Table 1 presents the stationarity of the BIST 100 return series.

Table 1. ADF and PP Stationarity Tests Results

	ADF test results		Phillips-Perron Test Results	
	Level		Level	
Return	(-9.12)	[0.00]*	(-15.31)	[0.000]*

Note. Data are analyzed within the framework of constant term and trend model. The parenthetical ( ) denotes the t-statistic value of the data, and the insides of square brackets [ ] denote the results of probability values. * indicates that the series is stationary at the 1% significance level. The critical values in question for ADF and PP are put forward by MacKinnon (1996).

Table 1 illustrates the ADF and PP test results of the return series. Accordingly, the results showed that the return series is stationarity at its level values. In the unit root tests in question, the null hypothesis states that the series contains a unit root and is not stationary, while the alternative hypothesis states that the series does not contain a unit root and is a stationary serial. In this context, it is concluded that the probability value of the tests (0.000) is smaller than 1%, which the alternative hypothesis is accepted in the 99% confidence interval. Table 2 illustrates test statistics for the selection of the appropriate ARMA model.

Table 2. ARMA Criteria

Model	LogL	AIC*	BIC	HQ
(3,3)(0,0)	723.744729	-4.902361	-4.801628	-4.862012
(3,4)(0,0)	723.940740	-4.896854	-4.783530	-4.851461
(4,3)(0,0)	723.919418	-4.896708	-4.783384	-4.851315
(4,4)(0,0)	724.824373	-4.896057	-4.770141	-4.845620
(3,1)(0,0)	719.013270	-4.883653	-4.808103	-4.853390
(2,0)(0,0)	716.522354	-4.880290	-4.829924	-4.860115
(2,1)(0,0)	717.110599	-4.877470	-4.814512	-4.852251
(2,2)(0,0)	717.131477	-4.870764	-4.795214	-4.840501
(1,1)(0,0)	715.959497	-4.876435	-4.826068	-4.856260

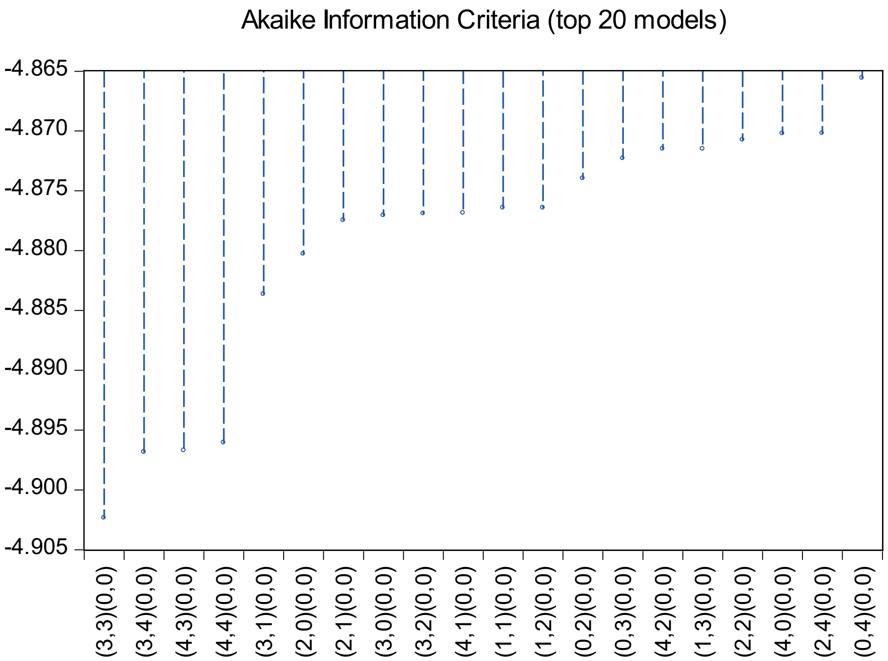


Table 2 illustrates appropriate ARMA model is AR (3) MA (3). Accordingly, an appropriate ARMA model will be used in Arch and GARCH applications of the series. Figure 2 illustrates the inverse roots of the ARMA polynomials used to determine the consistency of the selected ARMA model.

Figure 3. Inverse Roots of ARMA polynomials

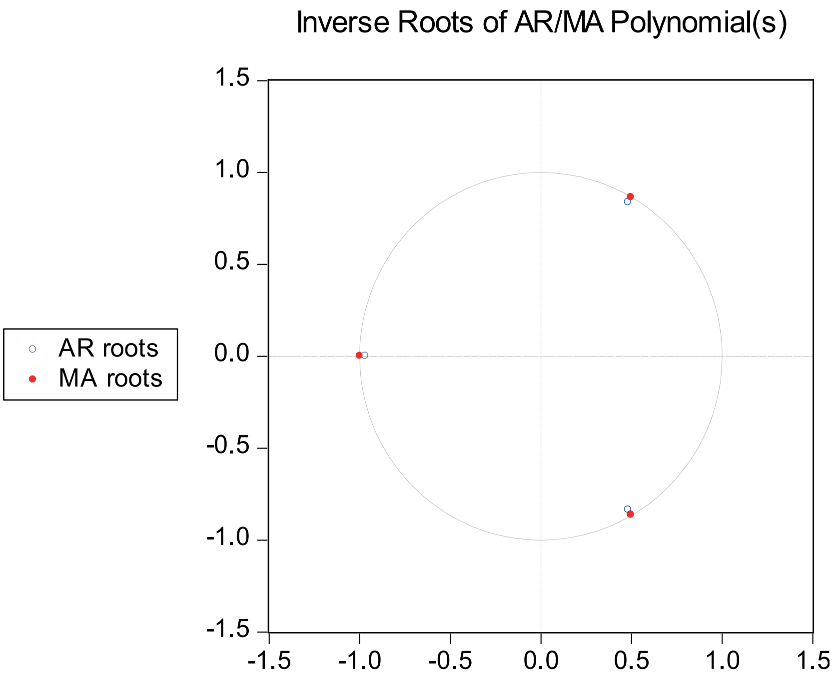


Figure 2 illustrates the selected ARMA model is consistent since the AR and MA roots are occupied inside the unit circle. Accordingly, autocorrelation and heteroscedasticity should be test respectively. The autocorrelation analysis of the series is examined by the Breusch-Godfrey Serial Correlation LM Test and the presence of autocorrelation as denoted in Table 3.

Table 3. Autocorrelation Test Results

Breusch-Godfrey LM Test	Probability Value Chi Square	Obs*R-squared
LM (k=1)	0.0162	5.779636
LM (k=31)	0.0070	53.64921

Table 3 illustrates null hypothesis is rejected as the probability value is smaller than 0.05. Therefore, the alternative hypothesis is accepted. In other words, there is an existence of autocorrelation in the return series. The presence of heteroscedasticity is a prerequisite to benefit from the ARCH-GARCH analysis set. ARCH-LM (Lagrange Multiplier-Lagrange Multiplier) test is used to investigate the heteroscedasticity condition of the series as denoted in Table 4.

Table 4. LM Test for Aautoregressive Conditional Heteroscedasticity (ARCH)

ARCH-LM Testi	Probability Value Chi Square	Obs*R-squared
LM (k=1)	0.0011	10.59395
LM (k=31)	0.0000	81.94844

To calculate volatility with ARCH-GARCH family models, the ARCH effect or conditional heteroscedasticity should be found in the series. The hypotheses of the relevant test are null hypothesis is no ARCH effect, alternative hypothesis shows the presence of ARCH effect. The $|\chi^2$ statistic $|<|$ Obs*R2 | equation is determined for all of the ARCH-LM test results, which were extended to 31 delays caused by lagging for the series. Following, the null hypothesis was rejected. The rejection of the null hypothesis means existence of an ARCH effect. In particular, the presence of the ARCH effect is described in the BIST 100 return series.

4.1. BIST 100 Index Volatility Forecast

ARCH(p), GARCH(p,q), EGARCH(p,q), and TGARCH(p,q) models are used to determine the volatility of the BIST 100 Index Series. Calendar anomalies are included in each model before the model forecasting. The equations of ARCH (3), GARCH (3,3), EGARCH (3,3), and TGARCH (3,3) are respectively, as follows:

ARCH (3);

$$h_t = \alpha_0 + \sum_{i=1}^{3} \alpha_i e_{t-i}^2 + \tau_1 D_1 + \tau_2 D_2 + \tau_3 D_3 + \tau_4 D_4 + \tau_5 D_{PH} + \tau_6 D_C \quad (11)$$

GARCH (3,3);

$$h_t = \alpha_0 + \sum_{i=1}^{3} \alpha_i e_{t-i}^2 + \sum_{i=1}^{3} \beta_i h_{t-i} + \emptyset_1 D_1 + \emptyset_2 D_2 + \emptyset_3 D_3 + \emptyset_4 D_4 + \emptyset_5 D_{PH} + \emptyset_6 D_C \quad (12)$$

EGARCH (3,3);

$$lnh_t = \alpha_0 + \sum_{i=1}^{3} \beta_i lnh_{t-i} + \sum_{i=1}^{3} \theta \frac{e_{t-i}}{\sqrt{h_{t-i}}} + \sum_{i=1}^{3} \gamma \left| \frac{e_{t-i}}{\sqrt{h_{t-i}}} \right| + \lambda_1 D_1 + \lambda_2 D_2 + \lambda_3 D_3 + \lambda_4 D_4 + \lambda_5 D_{PH} + \lambda_6 D_C \quad (13)$$

TGARCH (3,3);

$$h_t = w + \sum_{i=1}^{3} \alpha_i e_{t-i}^2 + \sum_{j=1}^{3} \beta_i h_{t-j} + \sum_{k=1}^{3} \gamma_k e_{t-k}^2 D_{t-k} + \varphi_1 D_1 + \varphi_2 D_2 + \varphi_3 D_3 + \varphi_4 D_4 + \varphi_5 D_{PH} + \varphi_6 D_C \quad (14)$$

In the study, conditional variance models are defined and tested within the framework of the above equations. Table 5 illustrates the volatility forecast results of the BIST 100 index.

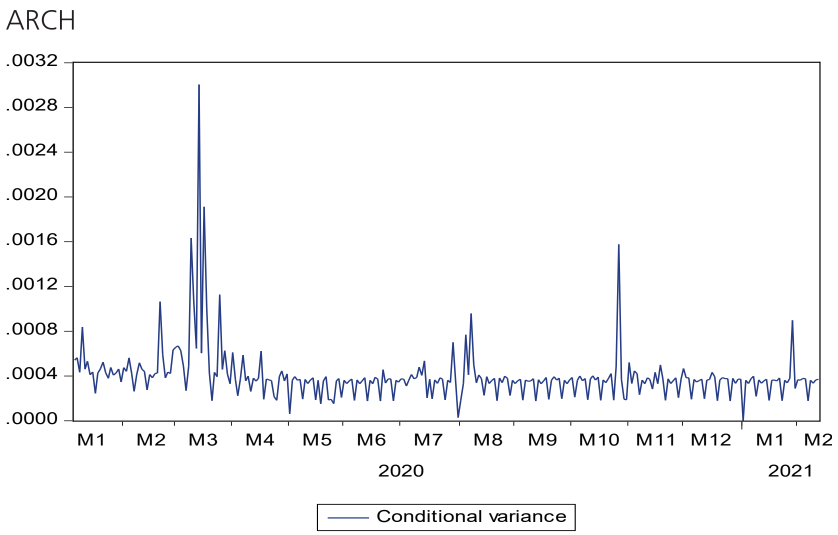
Table 5. BIST 100 Index Volatility Forecast Results

Dependent Variable: Return	ARCH	GARCH	EGARCH	TGARCH
Mean Equation				
Constant Term	-0.003	-0.003	0.002	-0.003
D_1	0.005	0.006	0.0006	0.005
D_2	0.003	0.001	0.0005	0.001
D_3	-0.003	-0.003	0.0001	-0.003
D_4	0.002	0.002	-0.0002	0.002
D_{PH}	-0.006	-0.005	-0.006***	-0.004
D_C	-0.003	0.007	0.003	0.007
AR (3)	0.008	0.004	0.009	0.005
MA (3)	0.010	0.012	-0.009	0.011
Variance Equation				
α_0	0.0004***	0.0003**	-7.673***	0.00003
α_1	0.1831***	0.1706***	-	0.143
γ	-	-	0.641***	0.071
θ	-	-	-0.356***	-
β_1	-	0.560***	0.079***	0.554***
w	-	-	-	-
D_1	0.0005	-0.0001	0.972***	-0.0001
D_2	0.0002	-0.0002	0.606***	-0.0002
D_3	0.0008	-0.0002	0.983***	-0.0002
D_4	-0.00017*	-0.0003**	-0.582***	-0.0002*
D_{PH}	-0.00018*	-0.0001***	-13.430***	-0.0001***
D_C	-0.00005	-0.0008	-0.690**	-0.00007
Info Criterions and ARCH				
LogLikelihood	752.09	769.02	841.22	769.07
AIC	-5.069	-5.179	-5.709	-5.172
SC	-4.864	-4.955	-5.468	-4.930
ARCH-LM (1)	0.636	0.826	0.907	0.944
ARCH-LM (31)	0.036	0.955	0.297	0.919

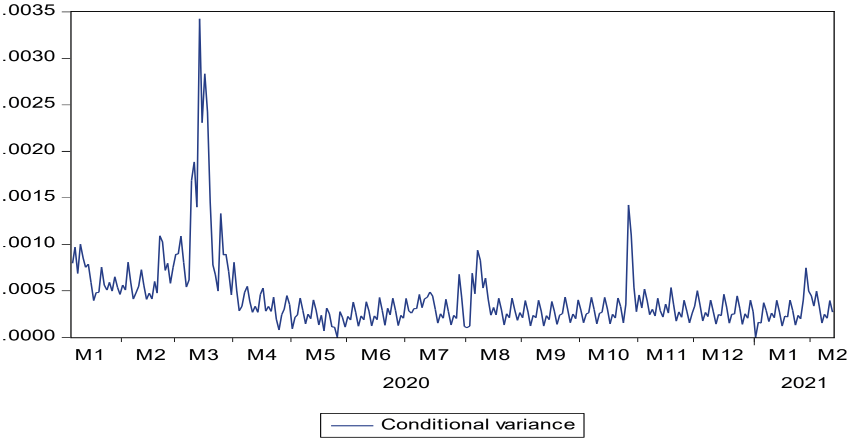
Note: ***, **, * denote 1%, 5%, and 10% significance level, respectively. All terms under mean and variance equations given are coefficients. While AIC is descriptive of Akaike Info Criterion, SC states Schwarz Criterion. The parenthetical ( ) denotes the number of lags. Terms in front of ARCH-LM present probability values.

The model results are evaluated according to Akaike, Schwarz, and Log-Likelihood criteria. The most suitable model for modeling the volatility in the return series is the EGARCH (3,3) model. Since EGARCH (3,3) has maximum Log-likelihood, minimum AIC (Akaike Info Criterion), and SC (Schwarz Criterion) values between models. It can also eliminate the heteroscedasticity issue. EGARCH and TGARCH models distinguish the effects of positive and negative shocks in the market and suggest producing results closer to reality. It is a prerequisite for the asymmetry condition in effects differentiation in shocks. Otherwise, the effects of negative shocks that cause more volatility than positive shocks are called the leverage effect. With regards to the EGARCH model, the θ coefficient is negative and statistically significant. The result in question reveals that the asymmetric effect is the leverage effect. In other words, the effect of negative shocks on the return series leads to higher volatility compared to positive shocks, which may have an asymmetric effect on stock returns. Contrarily, the day of the week and public holidays are included in all analyses as calendar anomalies. The COVID-19 pandemic has also attached the model. Under the one-year time limit analyzed for these models, while the effect of Monday, Tuesday, and Thursday on the volatility movements between days of the week is positive, the effect of Friday is negative. The effect of the public holiday anomaly on stock market returns is likewise negative. The COVID-19 pandemic may harm volatility movements. All of these results are statistically significant and convenient to interpret. Figure 3 illustrates the volatility distribution of the BIST 100 return index.

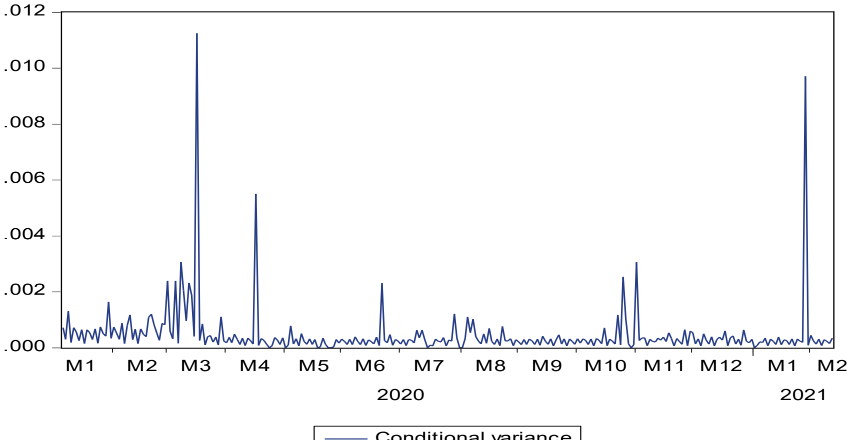
Figure 3: Volatility distribution of the BIST 100 Return Index



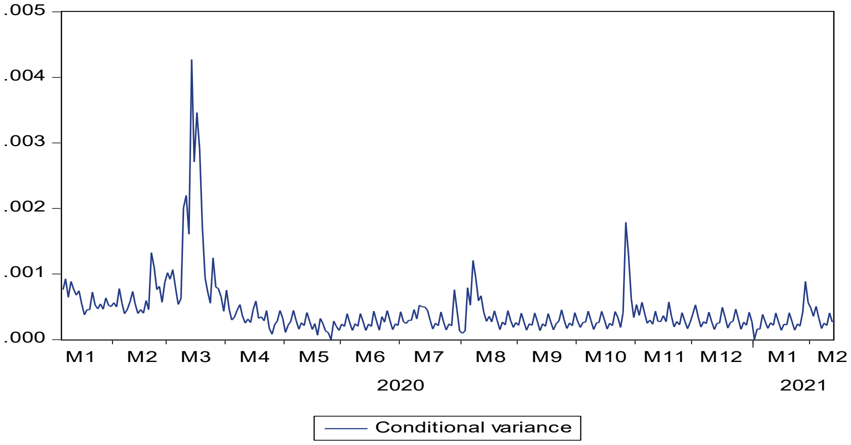
GARCH



EGARCH



TGARCH



In figure 3, volatility movements of the return series are excessive since the first case of the COVID-19 pandemic in Turkey is illustrated. Further, rises in volatility occur during periods of increase of cases. As is known, the volatility of the financial market tends to accelerate in an atmosphere of instability and uncertainty sensed by decision-making units or market actors in the economy. Based on the EGARCH model, negative shocks affect volatility at a higher level than positive shocks. In the COVID-19 pandemic, the global markets may increase the risk of perception, expectations of the recession in the world economy, the financial fragility of the base of the expansion, the deterioration in liquidity conditions. All are among the developments that marked last years. Consequently, the negative shocks cause increases in the volatility of the BIST 100 return series.

5. Conclusion

Financial markets originate from the historical slave exchanges and have a key role in the modern world. Financial markets that have a developed structure at this level further contain several dead ends. Among the dead ends in a question, the place of volatility movements that create the basis for uncertainty and risk is crucial. With the collapse of the Bretton Woods system, the transition of the world market toward a flexible exchange rate regime and the liberalization of capital movements may be seen as developments that marked the post-70s period. The liberalization process of capital movements includes productive capital and financial capital movements. The liberalization trend, which gained momentum in the financial markets of developed and developing countries as of the 1980s, causes the markets to adapt more to each other.

Developing countries may be areas where achievement of rising real returns for short-term capital movements. There are hypersensitive movements to an environment of uncertainty and risk combined with financial liberalization. Consequently, capitals meet an environment of uncertainty and risk after the country loses it speedily. That undoubtedly leaves the countries in question with structural savings deficits alone with the phenomenon of economic crisis. Therefore, portfolio-based foreign investors who come to the country after financial liberalization have undeniably influenced the volatility movements in the financial markets of developing countries. On the other side, volatility is high where there is an environment of uncertainty and risk. From this point of view, testing the volatility movements are vital to financial markets is becoming an essential need.

Among the analysis results, the EGARCH (3,3) model seems that the θ coefficient is negative and statistically significant. The results reveal that the asymmetric effect is the leverage effect. The effect of negative shocks on the return series leads to higher volatility compared to positive shocks, which may have an asymmetric effect on BIST-100 returns. Besides, Monday, Tuesday, Thursday and Friday, and public holidays are included in all analyses as calendar anomalies. Moreover, the COVID-19 pandemic has attached the model. Under the one-year time limit analyzed for these models, while the effect of Monday, Tuesday, and Thursday on the volatility movements between days of the week is positive, the effect of Friday is negative. On the other side, the effect of the public holiday anomaly on stock market returns is negative. The COVID-19 pandemic may increase volatility movements. To alleviate volatility movements, financial and real sectors must achieve a stable and strong structure in coordination. In addition, measures should be taken to prevent short-term capital movements. In the world, Tobin Tax was a traditional measure method applied temporarily against this situation. It is an indispensable need to develop more modern methods.

References

1. Adaramola, A. O., & Adekanmbi, K. O. (2020). Day-of-the-week effect in Nigerian stock exchange: adaptive market hypothesis approach. Investment Management & Financial Innovations, 17(1), 97.
2. Alagidede, P. (2008). Day of the week seasonality in African stock markets. Applied Financial Economics Letters, 4(2), 115-120.
3. Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. Applied Financial Economics, 18(15), 1201-1208.
4. Baker, H. K., Rahman, A., & Saadi, S. (2008). The day-of-the-week effect and conditional volatility: Sensitivity of error distributional assumptions. Review of Financial Economics, 17(4), 280-295.
5. Bayçelebi, B. E., & Ertuğrul, M. (2020). BIST Banka Endeksi Volatilitesinin GARCH Modelleri Kullanılarak Modellenmesi. Anadolu Üniversitesi Sosyal Bilimler Dergisi, 20(1), 233-244.
6. Berument, H., Coskun, M. N., & Sahin, A. (2007). Day of the week effect on foreign exchange market volatility: Evidence from Turkey. Research in International Business and Finance, 21(1), 87-97.
7. Berument, H., Kiyamaz, H., (2001). The day-of-the-week effect on stock market Volatility. Journal of Economics and Finance 25, 181-193.
8. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of econometrics, 31(3), 307-327.
9. Brooks, C. (2008). RATS Handbook to accompany introductory econometrics for finance. Cambridge Books.
10. Chand, S., Kamal, S., & Ali, I. (2012). Modeling and volatility analysis of share prices using ARCH and GARCH models. World Applied Sciences Journal, 19(1), 77-82.
11. Charles, A. (2010). The day-of-the-week effects on the volatility: The role of the asymmetry. European Journal of Operational Research, 202(1), 143-152.
12. Cho, Y. H., Linton, O., & Whang, Y. J. (2007). Are there Monday effects

in stock returns: A stochastic dominance approach. Journal of Empirical Finance, 14(5), 736-755.

13. Chukwuogor-Ndu, C. h. i. a. k. u. (2006). Stock market returns analysis, day-of-the-week effect, volatility of returns: Evidence from European financial markets 1997-2004. International Research Journal of Finance and Economics, 1(1), 112-124.

14. Çağıl, G., & Okur, M. (2010). 2008 Küresel Krizinin İMKB Hisse Senedi Piyasası Üzerindeki Etkilerinin GARCH Modelleri ile Analizi. Marmara University Journal of the Faculty of Economic & Administrative Sciences, 28(1).

15. Çil, N. (2018). Finansal ekonometri. Der Yayınları, İstanbul.

16. Diaconasu, D. E., Mehdian, S., & Stoica, O. (2012). An examination of the calendar anomalies in the Romanian stock market. Procedia Economics and Finance, 3, 817-822.

17. Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation. Econometrica, 50, 987- 1008.

18. Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. Econometric reviews, 5(1), 1-50.

19. GÜRİŞ, S., & Saçildi, İ. S. (2011). İstanbul Menkul Kıymetler Borsası'nda Hisse Senedi Getiri Volatilitesinin Klasik ve Bayesyen GARCH Modelleri ile Analizi. Trakya Üniversitesi Sosyal Bilimler Dergisi, 13(2), 153-171.

20. Kohers, G., Kohers, N., Pandey, V., & Kohers, T. (2004). The disappearing day-of-the-week effect in the world's largest equity markets. Applied Economics Letters, 11(3), 167-171.

21. Kohli, R. K. (2012). Day-of-the-week effect and January effect examined in gold and silver metals. Insurance markets and companies: analyses and actuarial computations, (3, Iss. 2), 21-26.

22. Kuzu S. (2018). BİST 100 Getiri Volatilitesinin ARCH ve GARCH Modeli ile Tahmin Edilmesi, Muhasebe ve Vergi Uygulamaları Dergisi Nisan 2018; Özel Sayı: 608-624.

23. Krężołek, D. (2018). Testing Day of the Week Effect on Precious Metals Market. Dynamic Econometric Models, 18, 81-97.

24. Lama, A., Jha, G. K., Paul, R. K., & Gurung, B. (2015). Modelling and forecasting of price volatility: An application of GARCH and EGARCH models. Agricultural Economics Research Review, 28(347-2016-17165), 73-82.

25. Magbame C.O. and Ikhatua J. O. (2013). Accounting Information and Stock Volatility in the Nigerian Capital Market: A GARCH Analysis Approach, International Review of Management and Business Research, Vol. 2 Issue. 1.

26. Mazibas, M. (2005). IMKB Piyasalarındaki Volatilitenin Modellenmesi ve Öngörülmesi: Asimetrik GARCH Modelleri Ile Bir Uygulama (Modeling and Forecasting Volatility in Istanbul Stock Exchange Markets: An Application with Asymmetrical GARCH Models). Available at SSRN 3008342.

27. Maqsood, A., Safdar, S., Shafi, R., & Lelit, N. J. (2017). Modeling stock market volatility using GARCH models: A case study of Nairobi Securities Exchange (NSE). Open Journal of Statistics, 7(2), 369-381.

28. Mishkin, F. S. (1996). Understanding Financial Crises: A Developing Country Perspective, Nber Working Paper Series, http://www.nber.org/

29. Mishkin, F. S. (1998). International Capital Movements, Financial Volatility and Financial Instability, NBER Working Paper Series, Working Paper No:6390, January

30. Mishkin, F. S. (2004). The Economics of Money, Banking and Financial Markets. Argosy Publishing, Seventh Edition, United States of America.

31. Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the Econometric Society, 347-370.

32. Obalade, A. A., & Muzindutsi, P. F. (2019). Calendar Anomalies, Market Regimes, and the Adaptive Market Hypothesis in African Stock Markets. Journal of Management and Business Administration. Central Europe, 27(4), 71-94.

33. Oğuzsoy, C. B., & Güven, S. (2004). Holy days effect on Istanbul stock exchange. Journal of Emerging Market Finance, 3(1), 63-75.

34. Osabuohien-Irabor, O. (2016). Day-of-the-week anomaly: An illusion or a reality? Evidence from Naira/Dollar exchange rates. CBN Journal of Applied Statistics, 7(1), 311-332.

35. Özden, Ü. H. (2008). İMKB Bileşik 100 Endeksi Getiri Volatilitesinin Analizi.

İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi. Yıl:7 Sayı:13 Bahar 2008 s.339-350

36. Pierre, E. F. S. (1998). Estimating EGARCH-M models: Science or art? The Quarterly Review of Economics and Finance, 38(2), 167-180.

37. Yavuz, N. Ç., Güriş, B., & Kıran, B. (2008). The month and holy days effects on the volatility of trade deficit: Evidence from Turkey. Journal of Economic and Social Research, 10(2), 67-84.

38. Yılmaz, N. K. (2019). ARCH ve GARCH Modelleriyle Standard & Poors 500 Endeksinde Rassal Yürüyüş ve Piyasa Etkinliğinin Analizi. İşletme Araştırmaları Dergisi, 11(3), 1559-1574.

39. Zakoian, J. M. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and control, 18(5), 931-955.