International Journal of Commerce and Finance, Vol 11., Issue 2, 2025, 53-79

Volatility Switching in The Initial Crisis Period of The Covid-19 Pandemic: Comparing Islamic Stock & Conventional Stock Indexes for Borsa Istanbul

**Ayben Koy (Corresponding Author)*

*** Güldenur Adıgüzel*

Submitted: *26.03.2025* ***Accepted:*** *12.06.2025* ***Published:*** *31.10.2025*

Abstract

The objective of this research is to examine the volatility structure of both Islamic and conventional indexes at Borsa Istanbul (BIST) in Turkey. Specifically, the study analyzes BIST's KATLM 30 (Islamic index), BIST 30, and BIST 100 Index and compares their return and risk performance during the initial crisis period of the COVID-19 pandemic. The research investigates the stock market's volatility structure under various conditions by utilizing the Markov regime switching autoregressive moving average generalized autoregressive conditional heteroskedasticity (MS-ARMA-GARCH) models with two regimes. The analysis aims to identify low and high volatility regimes in the stock indexes. The study shows that the returns of all three BIST indexes vary in terms of regime change. However, the changes in the conventional indexes (BIST 30 and BIST 100) are higher than those of the Islamic index, with losses during high volatility periods being almost 4-7 times greater than gains during low volatility periods. The research demonstrates that the change in returns from BIST 100 and BIST 30 between different regimes is higher than that of KTLM. In addition to comparing returns, the study also examines the resilience of both conventional and Islamic indexes during crises. These results provide insights into the behavior of stock market indexes during periods of economic turmoil and contribute to the existing literature on the subject.

Keywords*:* Markov switching, Islamic finance, Volatility, Borsa Istanbul

Jel Codes: G10, G11, G19

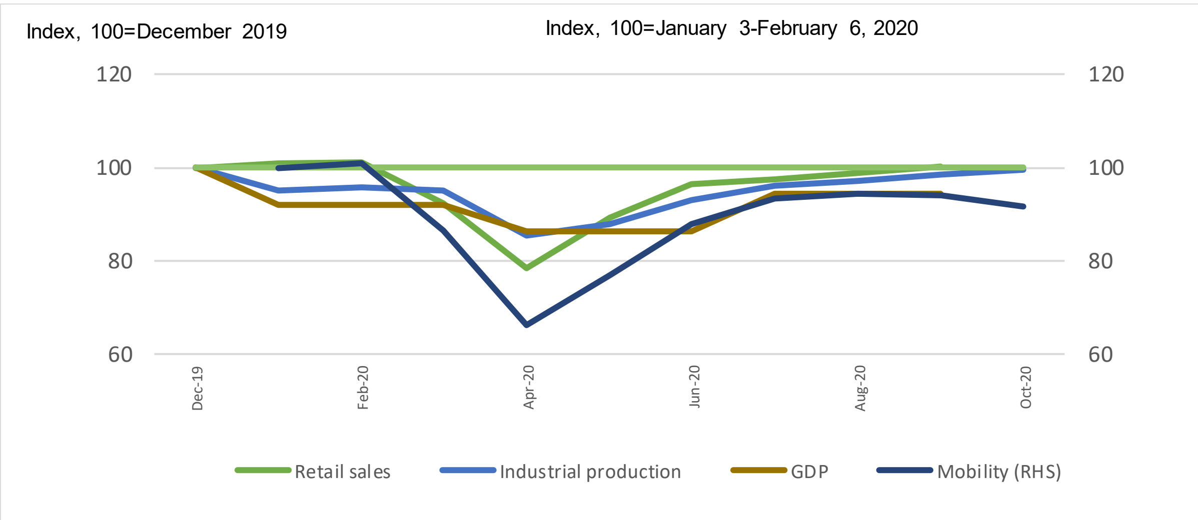
Department of Business Administration, Faculty of Economics, Administrative and Social Sciences, Fenerbahçe University, Istanbul, Türkiye, e-mail: ayben.koy@fbu.edu.tr, ORCID ID: 0000-0002-2506-6634

Department of Economics, Faculty of Business Administration, Istanbul Ticaret University, Istanbul, Türkiye, e-mail: gadiguzel@ticaret.edu.tr, ORCID ID: 0000-0003-3341-7016

Introduction

When examining the factors that influence the global economic system, theories and institutions may be the first things that come to mind. However, despite the growing prevalence of technological infrastructure, human beings still lie at the heart of economic formations, activities, and policies. Thus, the COVID-19 pandemic has had a direct impact on individual and societal health and has affected all areas of the economy. The restrictions and lockdowns implemented worldwide have damaged both supply and demand, leading to macro- and micro-level economic disruption. Furthermore, this crisis differs from previous ones in its emergence and development. It has simultaneously affected service sectors such as transportation, logistics, food, health, and tourism. The global economy has experienced intense shocks from both supply and demand sides. The World Bank (2021) has reported that the global economy shrank by 4.3% in 2020, and although growth is predicted to occur in 2021, it is expected to be lower than pre-pandemic levels. As of the time of writing, the epidemic statistics have worsened, with over 17 million people infected with the disease and approximately 700,000 deaths (Worldometer, 2020).

Figure 1. Global activity indicators.



Source: World Bank. (2021). *Global Economic Prospects*, *January 2021*. Washington, DC: World Bank. doi: 10.1596/978-1-4648-1612-3.

Global economic activity had been affected very deeply in 2020's first quarter when the pandemic began spreading all over the world. As seen in Figure 1, retail sales, industrial production, and mobility experienced very sharp declines. The initial period of the pandemic hit economies hard and recovery has yet to be sustained. This article aims to analyze this deep crisis period from the financial perspective.

While the effects from the 2008 global financial crisis are still ongoing, the new type of crisis COVID-19 has caused deeply affects both the real and financial sectors. Effects from economic crises on conventional financial markets are seen to have been studied in many ways in the literature (Porteba & Summers, 1986; French et al., 1987; Andersen et al., 2003). Islamic financial markets, interest in which has increased, have also been exposed to these crises in addition to conventional markets. Aside from banks operating with interest-free financial tools, Islamic indexes are designed to filter out the stocks in conventional indexes in accordance with the doctrinal position of the Islamic laws that present a number of ethical considerations for a stock to be considered ethically acceptable and have been established in different countries (Ho et al., 2014). These markets may be considered more fragile due to their limited size, and their structure is limited by ethical and religious values (Bauer et al., 2005). However, evaluating the performance of Islamic indexes, especially during crises, is important both for investors and portfolio managers.

Based on foundations different than conventional markets, Islamic markets are expected to behave differently toward crises. One supplementary fact is that the asset-backed rule in Islamic finance ensures a close linkage between the real and financial sectors; this allows Islamic emerging markets to not get exposed to volatility spillovers from conventional markets (Majdoub & Mansour, 2014, p. 453). Because companies included in Islamic equity indexes are supposed to have very low-leverage ratios and very minimal involvement in interest/usury, this is expected to break the link with financial economic volatility. Islamic financial tools are more socially responsible than conventional tools and will attract more investors who want to invest for ethical and religious reasons in particular (Dharani & Natarajan, 2011). These tools are also stated to be less volatile due to their nature (Ahmad & Alsharif, 2019). Some scholars strongly argue that, despite being nascent in nature, Islamic finance has great potential in addressing the challenges from global financial markets such as financial crises (Chapra, 2011).

Due to the approach that Islamic indexes should have a more reliable and robust structure, discussions in the literature about how its returns will be are widely available (Hakim & Rashidian, 2004; Elfakhani et al., 2005; Hussein, 2007; Walkshäusl & Lobe, 2012; Ho et al., 2014; Al-Khazali et al., 2014; Rizvi & Arshad, 2018). However, the fragility and sensitivity these indexes have against crises have not been adequately addressed. Although their returns are stable in normal periods, resistance or fluctuations during a crisis will have greater effects on investors. For this reason, their effectiveness during crises should be investigated by comparing them with conventional indexes using a detailed analysis. The limited studies in the literature comparing Islamic indexes and their conventional counterparts have shown various results (Miniaoui et al., 2015). Hkiri et al.'s (2017) study on the Gulf Cooperation Council claimed Islamic indexes to fluctuate less and to be able to be considered as a kind of safe haven. In this context, our study examines the volatility structure of Islamic and conventional indexes in the BIST stock market across different regimes with the help of Markov regime-switching (MRS) models. How long the economic problems COVID-19 has caused will last remains unclear. The fluctuations and uncertainties caused by the shocks that have emerged in markets worry investors. In the face of this crisis, evaluating the performance of conventional stock indexes is necessary using the participation index formed according to Islamic criteria. The study's results are believed able to be a guide for investors' portfolio choices. Beyond comparing frequent returns in the literature, this study deals with the resistance conventional and Islamic indexes have had during crises. Secondly, no study dealing with BIST is found on this issue. Turkey is a rising Muslim economy, despite its many financial problems and the volatilities its stock exchange market faces. As such, studying and comparing Turkish Islamic indexes with conventional ones is of interest. Lastly, using MS-ARMA-GARCH modeling in the article also contributes to the Islamic finance literature by analyzing and comparing Islamic indexes and their counterparts.

2. Literature Review

Macroeconomic variables highly affect the stock market and, due to financial markets' important role in economic growth, have been subject to much research. However, when analyzing the functioning mechanism of financial markets, their level of fragility against crises draws attention. At this point, whether the Islamic financial system has higher resilience to crises or not is an honest question asked by those interested in macroeconomy. Many researchers looking for this question's answer have comparatively analyzed conventional and Islamic indexes.

Ho-Fun et al. (2014) investigated the performance of Islamic indexes compared to their conventional counterparts during both crisis and non-crisis periods. Their study revealed that Islamic indexes outperformed conventional ones during crisis periods, but the results for non-crisis periods were inconclusive. Al-Khazali et al. (2014) used stochastic dominance analysis to compare the performance of nine Dow Jones Islamic indexes with their conventional counterparts during the 1996–2012 and 2001–2006 periods. They found that Islamic indexes outperformed conventional ones during the global financial crisis, and Islamic investing performed better than conventional investing during the economic meltdown. Shamsuddin (2014) demonstrated that Islamic equity portfolios were less exposed to interest-rate risks than the Dow Jones Global Indices, particularly at the sectoral level. Dewandaru et al. (2014) examined a panel annual data of 11 primary Islamic countries compared to developed countries between 1996 and 2011. The results demonstrate that all the macroeconomic determinants we considered play a significant role in developed countries. In contrast, financial openness has a considerably smaller impact on Islamic countries, whereas financial intermediary development has a major influence. They found that Islamic markets were less vulnerable to exposure to recent crises due to their low leverage effect and less diversified portfolio structures. Analyzing Islamic indexes, Alam and Ansari (2020) provided slightly superior performance based on risk-adjusted performance measures, while Jawadi et al (2014) compared the financial performance of Islamic and conventional indexes in the USA, Euro area, and globally during both stable and turbulent periods. Various performance ratios were used, taking into account different types of risk (total, systematic, and specific) and restrictions (such as normal distribution and time-varying risk). They found that Islamic funds outperformed conventional ones since the subprime crisis began and during turbulent times. Ahmad et al. (2019) revealed that Islamic mutual funds (IMFs) were affected differently than conventional mutual funds (CMFs) during the 2008-2009 financial crisis, with IMFs limiting the negative impact on profitability due to their business model-related factors. Nevser et al. (2019) found no significant difference between returns from Islamic and conventional indexes or Islamic indexes and their counterparts. Ata and Buğan (2015) uncovered a causal relationship between market indexes at different time intervals and asymmetric information phenomenon in Morgan Stanley market indexes. The absence of certain factors in the Islamic financial system led to a more reliable financial system during the global financial crisis. Finally, Kayed and Hassani (2011) view the crisis as a real test of the Islamic financial system's ability to manifest itself.

Aloui et al. (2016) conducted a study to explore the co-movement between investors' sentiment and Islamic and conventional equity returns in the US market across various time scales and frequencies. They discovered a time-varying co-movement for both Islamic and conventional indexes, and the Sharia rules had no effect on the relationship between sentiment and Islamic equity returns. In another study, Hoque et al. (2016) used the MSCI Global Islamic Indexes to investigate the relationship between Islamic and conventional equity indexes. They found that although there were fundamental differences between the two markets, they moved together. However, the Islamic indexes were more volatile during the crisis period and less volatile during the post-crisis period. Meanwhile, Hassan and Girard (2019) analyzed seven indexes selected from the Dow Jones Islamic Market Index (DJIM) in comparison to their non-Islamic counterparts using various measures. They found no significant difference between the Islamic and non-Islamic indexes as Dow Jones Islamic indexes outperformed conventional indexes from 1996 to 2000 but underperformed from 2001 to 2005. Overall, both Islamic and conventional indexes offer reward benefits similar to those of risk and diversification.

The initial studies (Al-Awadhi et al., 2020, Onali, 2020; Seven and Yilmaz, 2020; Zhang et al., 2020) suggested that in the first Quarter of 2020, stock markets experienced a decline in returns and an increase in volatility due to the Covid-19 outbreak. Analyzing all the stocks listed on the Hang Seng Index and Shanghai Stock Exchange Composite Index during the COVID-19 outbreak in China, Al-Awadhi et al. (2020) discovered that the pandemic had an adverse impact on stock market returns. More specifically, the daily growth in total confirmed cases and total cases of death caused by COVID-19 were both significantly and negatively correlated with stock returns. An alternate body of research demonstrated that the decline in the stock market was not consistent and relied on the risks associated with the underlying assets. Seven and Yılmaz (2020) shows that larger fiscal rescue packages are linked to stronger equity market recovery during the pandemic. The COVID-19 related death rate has a negative correlation with the recovery rate, indicating its impact on investment decisions. Moreover, countries heavily reliant on natural resources and tourism revenues tend to have slower recovery. Various studies found that firms with lower leverage, higher liquidity, and stronger environmental and social ratings were less severely affected by the outbreak (Ramelli and Wagner, 2020). In another study, Heyden and Heyden (2020) investigated that the stock price reaction to the Covid-19 outbreak depended on firm-specific characteristics such as assets tangibility, liquidity, and institutional holdings. The findings indicate that stock markets respond in distinct ways to the announcement of the first case versus the first death in a country. Although there is no significant response to the first case, the declaration of the first death results in considerably negative reactions.

More recently, Hasan et al (2021) analyzed how COVID-19 pandemic affected the Islamic and conventional stock markets. The results show that the pandemic causes identical volatility in both of the markets since they are strongly linked and tend to co-move during the pandemic.

As a similar study, Chowdhury et al (2021) investigated a research on Islamic equity markets and their counterparts, conventional markets, in the Covid-19 age by using maximum drawdown-based risk measures. The results of the study indicate that Islamic markets recover more quickly and with a lesser degree of drawdown than non-Islamic markets. Smolo et al (2022), examined the degree of connectedness and spillover effect between and across emerging economies (BRICS and Turkey) Islamic and conventional equity markets, focusing on global crises. Daily frequency data (the period of 2002-2021) and Wavelet Coherence methodology are employed. The empirical findings of the study reveals that the comovements of these markets strengthen during the Global Financial Crisis and Covid-19 pandemic and the link is stronger in the conventional markets than Islamic markets. The results of the studies are in line with the Bossman et al (2022). Based on these findings, we anticipate that if Shariah compliant companies were perceived as safer by investors, their decline in stock prices in response to Covid-19 confirmed cases and government social distancing measures would be less severe.

3.Data and Methodology

We have used 121 daily observations for the period from January 2 to June 25, 2020. The period includes the collapse and recovery periods in the stock markets for the initial crisis period of the COVID-19 pandemic. We analyze the Katilim (KATLM), BIST 30, and BIST 100 indices on Borsa Istanbul, comparing the return and risk performances during the pandemic. All three indexes used in the sample have been equally weighted, with a rebalancing frequency of three months.

KATLM is a BIST index with 30 stocks traded on the Stars Market. It is the oldest among the three price indexes calculated from the companies accepted as suitable for investment in terms of Islamic finance. KATLM has been calculated since January 12, 2008, and the newer indexes (Participation 50 Index/KAT50 and Model Portfolio/KATMP) have been calculated since July 9, 2014. Three main criteria exist for being included in the BIST Islamic indexes. The first criterion is that the interest loans of the companies selected for the index are 30% below their market value. Secondly, a company's cash returns from interest should be less than 30% of its market value. Lastly, its income from unsuitable activities (unsuitable for Islam) should total less than 5%.

We've selected BIST30 and BIST100 as the conventional indexes. BIST30 consists of 30 stocks selected among companies traded on the Stars Market. BIST100 is used as the main index for the Borsa Istanbul Equity Market. It consists of 100 stocks selected among companies traded on the Stars Market. Moreover, BIST100 automatically includes BIST30.

We've analyzed the low and high volatility regimes of the stock indexes using Markov regime-switching autoregressive moving average generalized autoregressive conditional heteroskedasticity (MS-ARMA-GARCH).[1]

The MS-ARMA-GARCH models need to be tested over stationary series. We examine the logarithmic differences among the stationary variables using the Augmented Dickey–Fuller (ADF), Philips–Perron (PP), and Kwiatkowski-Philips-Schmidt-Shin (KPSS) unit root tests.[2]

Table 1. Descriptive Statistics

	KTILIM	BIST30	BIST100
Mean	133169.7	126923.5	106779.2
Median	137512.3	127104.7	109155.4
Maximum	152719.2	149678.7	123556.1
Minimum	95957.61	101409.7	84246.17
Std. Dev.	13832.31	13879.13	11229.14
Skewness	-0.951826	0.024777	-0.243039
Kurtosis	3.190777	1.747280	1.883899
Jarque-Bera	18.45393	7.924305	7.471519
Probability	0.000098	0.019022	0.023855
Sum	16113532	15357744	12920278
Sum Sq. Dev.	0.000000	0.000000	1.51E+10
Observations	121	121	121

According to the results, the first-level differences of the natural logarithmic variables should be used. After determining the stationary series, we selected the lag orders for ARMA for each series.[3]

[1] MS-ARMA-GARCH models tested in Oxmetrics.
[2] Unit root tests are applied in E-Views. The results appear in the Appendix.
[3] These results appear in the Appendix.

Descriptive statistics for the variables are shown by level in Table 1. While KTILIM (-0.9518) and BIST100 (-0.2430) are left-skewed; BIST30 (0.0248) is right-skewed. The kurtosis values for BIST30 and BIST100 are less than 3; these series have lighter tails than a normal distribution (i.e., they have light-tailed distributions). Meanwhile, the kurtosis value for KTILIM is greater than 3. KTILIM has a heavier-tailed distribution.

The autoregressive conditional heteroscedasticity model (ARCH) was developed by Engle (1982) to estimate variances for financial assets. Bollerslev (1986) expanded on this model,

creating the generalized autoregressive conditional heteroskedasticity model (GARCH). GARCH-class models aim to capture various features of financial time series, such as extreme plausibility and fat tails, beyond future volatility clusters.

In GARCH models, the variance in error terms is influenced by both their past values and the values of their conditional variance. This feature was developed by Bollerslev (1986) and Taylor (1986).

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{1}$$

GARCH models have proven effective in modeling variances and exploring different features of developing time series. The linear GARCH models include threshold GARCH (TGARCH; Zakoian, 1994), Glosten-Jagannathan-Runkle GARCH (GJRGARCH; Glosten et al., 1993), integrated GARCH (IGARCH; Nelson, 1990), fractionally integrated GARCH (FIGARCH; Baillie et al., 1996), and GARCH in mean (GARCH-M; Engle et al., 1987).

The exponential generalized autoregressive conditional heteroscedastic (EGARCH; Nelson, 1991) model was the first to examine nonlinearity in a GARCH model. Other nonlinear GARCH models include logistics smooth transition GARCH (LSTGARCH; Hgerud, 1997; Gonzalez-Rivera, 1998), volatility switching GARCH (SGARCH; Fornari & Mele, 1997), asymmetric nonlinear smooth transition GARCH (ANST-GARCH; Anderson et al., 1999), and quadratic GARCH (QGARCH; Sentana, 1995).

This study aims to examine the volatility of BIST indices through the application of Markov-switching GARCH (MS-GARCH) models. The framework for MS-GARCH models, which assess financial markets in terms of high and low volatility, was first introduced by Klaassen (1999) and further developed by Kim (1993), Cai (1994), Hamilton and Susmel (1994), and Dueker (1997). Markov regime-switching (MRS) models, which were initially proposed by Hamilton (1989), are also employed in this study. These models allow for the observation of time series variables, while the underlying regime of the market is not directly observable, and can be estimated through probabilities. By using the probability of regime-switching, it is possible to estimate the next state (s1) if the previous state (s0) is known (Bildirici et al., 2010). The MRS model involves a time series process that is based on an unobservable regime variable (st; Krolzig, 2000).

The regime-generating process is an ergodic Markov chain (Krolzig, 2000) where $p_{ij} = P_r(s_{t+1} = j|s_t = i)$; $\sum_{j=1}^{m} Pij = 1$; $i, j = \{1,..,m\}$, and s_t follows an ergodic M-state Markov process with an irreducible transition matrix:

$$\boldsymbol{P} = \begin{vmatrix} p_{11} & \cdots & p_{1m} \\ \cdots & \cdots & \cdots \\ p_{m1} & \cdots & p_{mm} \end{vmatrix} \tag{2}$$

The Markov-switching autoregressive moving average generalized autoregressive conditional heteroskedasticity (MS-ARMA-GARCH) model is characterized by a conditional mean, a conditional variance, a regime process, and a conditional distribution, which are standard components of a typical MS-GARCH model (Marcucci, 2005; Günay, 2015). In this study, we adopt the MS-ARMA-GARCH model methodology.

While y_t is the dependent variable in the ARMA model, h_t is its conditional variance; the parameters $\emptyset, \theta, \alpha,$ and β depend on the state of the Markov chain. The formulas in the ARMA-GARCH model are as follows:

$$y_t = C_{s_t} + \varepsilon_t + \sum_{i=1}^{r} \emptyset_i(S_t) y_{t-i} + \sum_{j=1}^{m} \theta_j(S_t) \varepsilon_{t-j} \tag{3}$$

$$h_t = w_{S_t} + \sum_{i=1}^{q} \alpha_i(S_t)\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j(S_t)\, h_{t-j} \tag{4}$$

$$\varepsilon_t = \sqrt{h_t} * u_t \,;\, u_t \sim N(0,1) \tag{5}$$

3.1. Empirical Results

In this study, we utilized MS-ARMA-GARCH models with two regimes to investigate the low and high volatility regimes of stock indexes. The estimation procedure used Regime 0 to represent low volatility and Regime 1 to represent high volatility. In ARMA models, regimes are separated into expansion (Regime 0) and recession (Regime 1) periods.

Two models were used to estimate the switching mechanism between low and high volatility periods, with the only difference between the models being the inclusion of autoregressive moving average (ARMA) variables. In the first model, the switching component was only the constant in the ARMA model, while in the second model, both the autoregressive and moving average components switched between low and high volatility periods in addition to the constant. Despite this difference, both models estimated the variance equation using three switching components: the constant, the alpha, and the beta.

For KATLM, the ARMA model selected was AR(2), while for BIST30 and BIST100, the selected model was AR(3)-MA(1). The estimated equations for KATLM are presented in Table 2, where Model 1 is the MS(2)-ARMA(2,0)-GARCH model with a switching constant in the ARMA equation. According to Model 1, the return on the low volatility regime was described through the first and second autoregressive components (0.094716 for AR(1) and 0.085046 for AR(2)), while the autoregressive components in Model 2 were not significant. Furthermore, the Akaike information criterion (AIC) and Schwarz information criterion (SIC) indicated that Model 1 was stronger than Model 2.

The constant in the ARMA equation for the low volatility regime had positive values for both Models 1 (0.004082) and 2 (0.004067), while the coefficient in the high volatility regime was negative for both models (Model 1: -0.009563 and Model 2: -0.010743); all were significant in the ARMA equations. As evidenced by the coefficients, losses during high volatility periods were on average twice as large as gains during low volatility periods.

Variance equations for KATLM indicate the coefficient for the constant in Model 1 to approach zero for both Regimes 0 and 1. However, the coefficient for the constant in the high volatility regime in Model 2 is slightly higher (0.003069). The alpha, which is the coefficient for the residual square, is significant only for Regime 0 in Models 5 (α = 0.028290) and 6 (α = 0.025059).

Two of the regimes in Models 5 and 6 exhibit significant beta coefficients. This suggests that it is possible to statistically explain the volatility of the index by past volatility values during both low and high volatility periods. In Model 1, the coefficient for the constant in the low volatility period (0.9283) is higher than that in the high volatility period (0.9232). Conversely, in Model

2, the coefficient in the high volatility period (0.9432) is higher than that (0.9309) in Regime 0. The results do not provide any general evidence indicating that the conditional variance varies over the low and high volatility periods for KATLM.

Transition probability represents the likelihood that the indexes will stay in their original regime. Both transition possibilities in Models 1 and 2 for KATLM indicate that 99% stays in the low volatility regime when KATLM is in Regime 0 (low volatility), with only 1% having the probability of switching to the high volatility regime. The probability of staying in the high volatility regime (94%) is lower than the probability of staying in the low volatility regime (99%).

Table 2. Equations, Probabilities and Information Criteria for Models 1 and *2*

Model 1: KATLM 1			**Model 2: KATLM 2**		
	Regime (0)	**Regime (1)**		**Regime (0)**	**Regime (1)**
ARMA Equation			**ARMA Equation**		
AR(1)	0.094716*** (0.094970)		AR(1)	0.083446 (0.103600)	0.150079 (0.221700)
AR(2)	0.085046*** (0.090820)		AR(2)	0.0261532 (0.106100)	0.284783 (0.1966)
Constant	0.004082* (0.001327)	-0.009563* (0.007591)	Constant	0.004067* (0.001234)	-0.010743** (0.01042)
Variance Equation			**Variance Equation**		
Constant	0.000000* (0.001554)	0.000000** (0.012700)	Constant	0.000000* (0.001692)	0.003069** (0.013790)
Alpha	0.028290** (0.012430)	0.173992 (0.172300)	Alpha	0.025059* (0.012670)	0.106968 (0.170200)
Beta	0.928263** (0.016820)	0.923228*** (0.094420)	Beta	0.930883* (0.017350)	0.943190*** (0.056740)
Transition Probabilities			**Transition Probabilities**		
p_{0|0}	0.987110		p_{0|0}	0.987027	
p_{1|1}	0.940674		p_{1|1}	0.943011	
Information Criteria			**Information Criteria**		
log-likelihood 327.856836	AIC -5.353506	SC -5.071741	log-likelihood 328.533896	AIC -5.331083	SC -5.002358

Note: *, **, *** represent respectively 0.1, 0.05 and 0.01 significant levels.

The values in parenthesis represent standard errors.

Alpha and beta coefficients represent respectively ARCH and GARCH parameters.

The smoothed regime probabilities for Models 1-6 are respectively given in Figures 1-6. The shaded areas on the left side of the figures correspond to low volatility regimes, with the remaining areas relating to high volatility regimes. The opposite is valid for the right side, as the shaded areas are regime 1 with high volatility.

In this study, the figures show regime periods with high volatility to include periods in which the stock markets had experienced collapse during the epidemic.

Figure 2. Smoothed regime probabilities: Model 1.

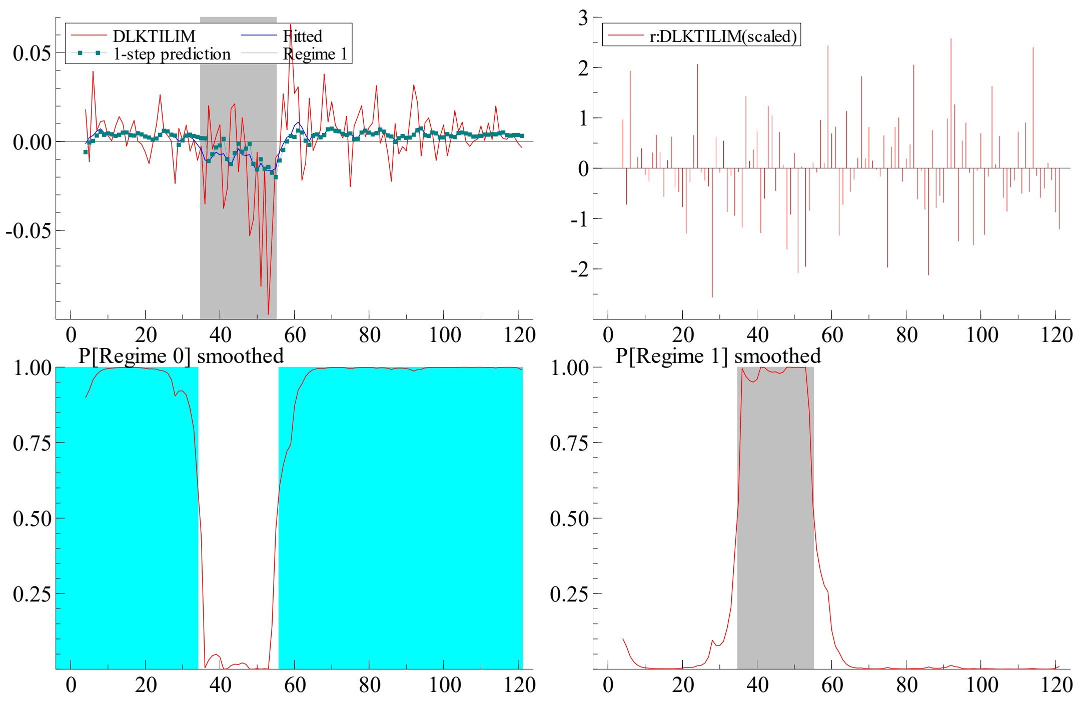


Figure 3. Smoothed regime probabilities: Model 2**.**

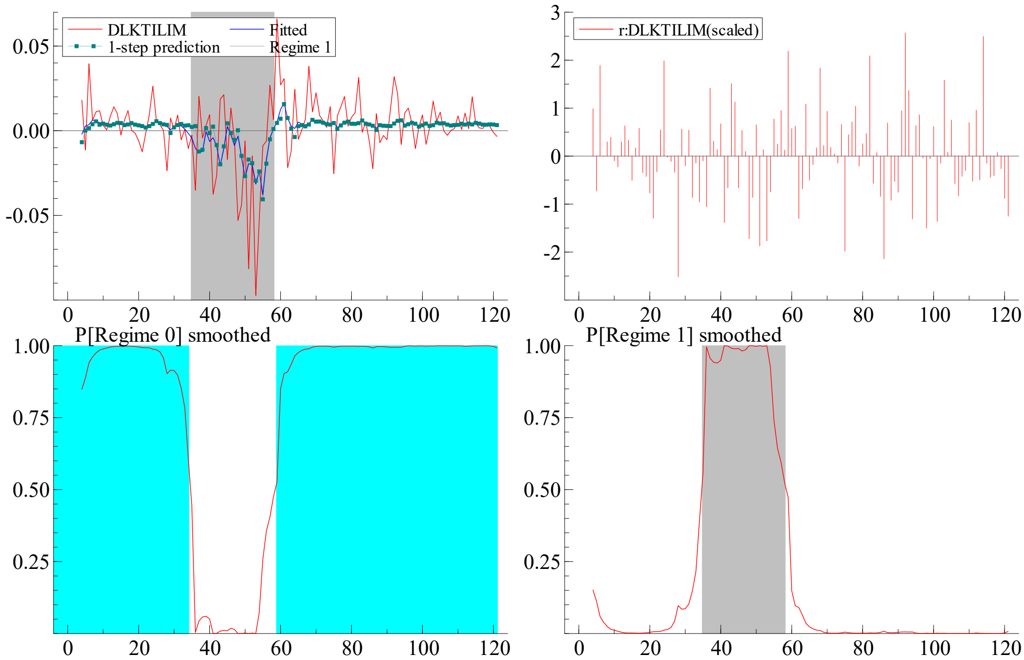


Table 3 show the models estimated for BIST30. Model 3 is the MS(2)-ARMA(3,1)-GARCH model with a switching constant in the ARMA equation, and Model 4 contains the other four switching components. Aside from the constants, only one component of ARMA in both models, AR(3), is positive and significant (0.121555) in Regime 0 from Model 3.

The constant in the low volatility regime is positive for Models 3 (0.001421 and 4 (0.003753), the coefficient in the high volatility regime is negative for Models 3 (-0.005663) and 4 (-0.027487), with all being significant in the ARMA equations. The findings for BIST30 are significant because the losses in high volatility periods are nearly 4 to 7 times higher than the gains in low volatility periods in terms of absolute values.

When examining the variance equations for the BIST30 index during the observation period, the coefficients for the constant are observed to vary greatly from one another among regimes in terms of value (0.006838 from Regime 0 to Regime 1 and 0.027056 from Regime 1 to Regime 0) for Model 3; 0.006494 (from Regime 0 to Regime 1) and 0.018316 (from regime 1 to regime 0) for Model 4. The constant coefficients in Regime 1 are approximately 3-4 times greater than those for Regime 0. The findings show a very high difference in volatility to exist between the regimes for BIST30.

While only one alpha coefficient is significant in Models 3 and 4, the other alpha coefficient and the beta coefficients have insignificant values; as such, the high difference in volatility during the crisis cannot be explained by past values or conditional variance.

The probability of staying in the low volatility regime for BIST30 is 99% for both Models 3 and 4. When BIST30 is in the high volatility regime, the probability is 94% (Model 4) to 95% (Model 3) that it will stay in the same regime in the next observation.

Table 3. Equations, Probabilities, and Information Criteria for Models 3 and 4

Model 3: BIST30 1			**Model 4: BIST30 2**		
	Regime (0)	**Regime (1)**		**Regime (0)**	**Regime (1)**
ARMA Equation			**ARMA Equation**		
AR(1)	-0.789372 (0.166500)		AR(1)	0.517535 (0.309400)	0.298109 (0.152000)
AR(2)	0.069473 (0.125500)		AR(2)	-0.019790 (0.111400)	0.383372 (0.144800)
AR(3)	0.121555*** (0.089290)		AR(3)	0.096331 (0.098640)	-0.511471 (0.174800)
MA(1)	0.796639 (0.139700)		MA(1)	-0.494626 (0.288700)	-0.538203 (0.203200)
Constant	0.001421* (0.000809)	-0.005663* (0.004190)	Constant	0.003753* (0.003492)	-0.027487** (0.017130)
Variance Equation			**Variance Equation**		
Constant	0.006838* (0.002352)	0.027056** (0.022970)	Constant	0.006494* (0.001695)	0.018316** (0.02313)
Alpha	0.000000 (0.110200)	0.000000 (0.335200)	Alpha	0.000000** (0.028850)	0.000000 (0.490100)
Beta	0.641080 (0.219500)	0.197405 (1.427000)	Beta	0.664496 (0.166400)	0.672046 (0.6400)
Transition Probabilities			**Transition Probabilities**		
p_{0|0}	0.985357		p_{0|0}	0.987144	
p_{1|1}	0.947636		p_{1|1}	0.936577	
Information Criteria			**Information Criteria**		
log-likelihood 321.841977	AIC -5.262256	SC -4.931740	log-likelihood 325.445832	AIC -5.255484	SC -4.830535

Note: *, **, *** represent respectively 0.1, 0.05 and 0.01 significant levels.

The values in parenthesis represent standard errors.

Alpha and beta coefficients represent respectively ARCH and GARCH parameters.

Figure 4. Smoothed regime probabilities: Model 3.

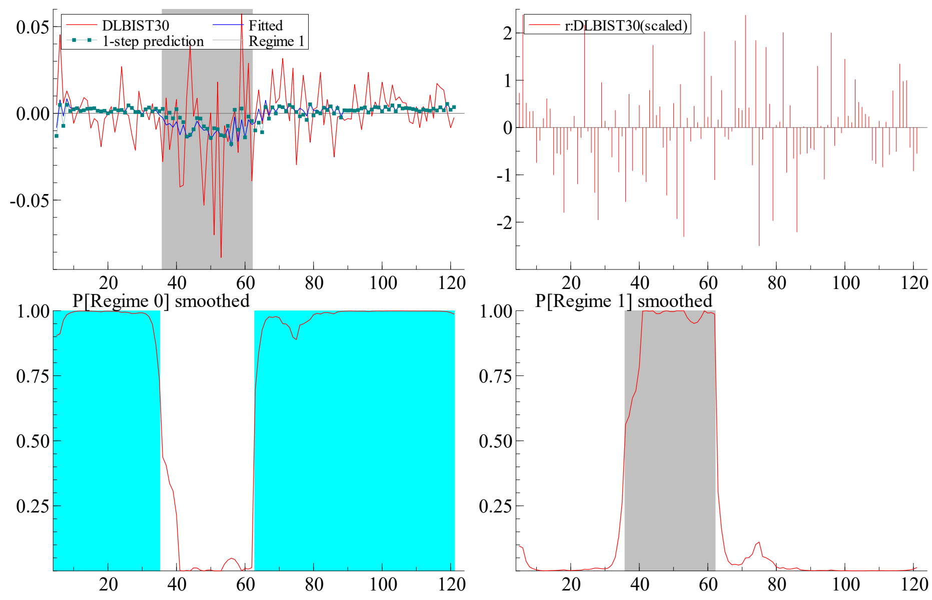
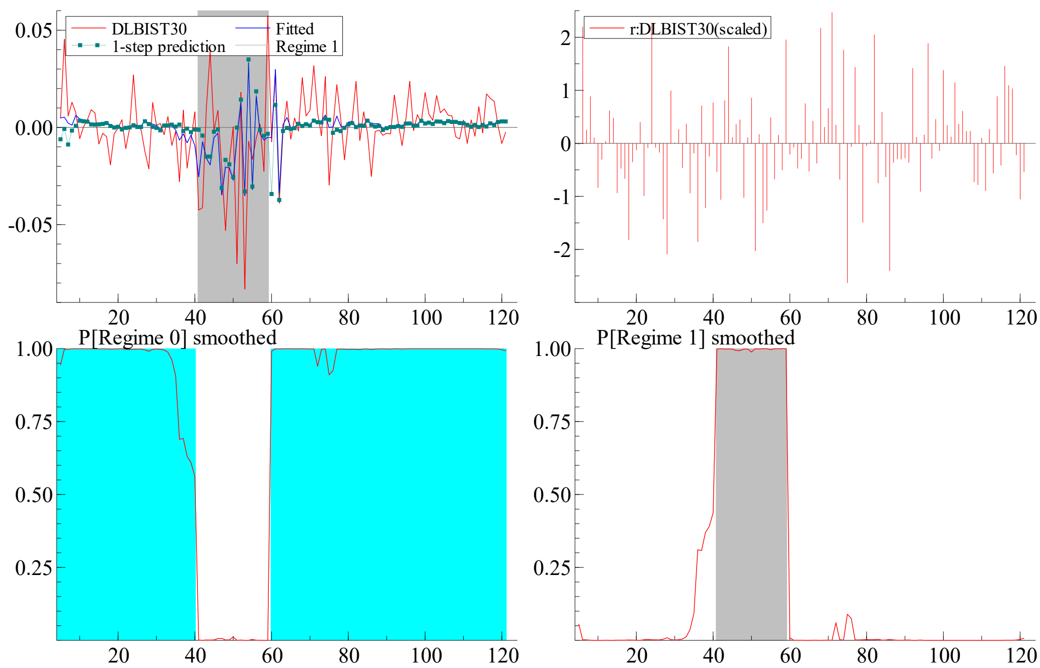


Figure 5. Smoothed regime probabilities: Model 4.



Two equations have been estimated for BIST100, with the results given in Table 3. Model 5 is the MS(2)-ARMA(3,1)-GARCH model with a switching constant in the ARMA equation, while Model 6 has the other switching ARMA components. Model 5 has only two variables from the ARMA equation that are significant: 0.092741 for AR(3) and 0.841060 for MA(1). Model 6 has only one significant component in the low volatility regime in addition to the constant: 0.095799 for AR(3).

As seen in the models from the KATLM and BIST30 indices, the model where the ARMA components do not switch (Model 5) is stronger than Model 6, where the ARMA components switch with respect to the AIC and SIC criteria.

As investigated in the other models, the absolute values for losses in high volatility periods are greater than the gains in the low volatility regimes. The constants have positive coefficients for both Models 5 (0.001806) and 6 (0.005883); these coefficients have lower absolute values than the coefficients from the high volatility regimes, with |-0.006185| for Model 5 and |-0.023158| for Model 6. The absolute values of the losses in high volatility periods are nearly 3 to 4 times higher than the gains in low volatility periods. Although the differences between coefficients is not as high as in BIST30, the difference between coefficients among regimes is higher than those for KATLM. These results provide evidence that the difference in returns for BIST100 between different regimes is higher than the differences in returns for KTLM but not high as those for BIST30.

Comparing is difficult because the significant variables in the variance models from BIST100 differ between both models and regimes. The coefficients for the constant in the variance equation in Models 5-6 are approach zero for both Regimes 0 and 1. Interestingly, the coefficients for the constant in low volatility periods are slightly higher (0.001419 for Model 5 and 0.006486 for Model 6). While the coefficients for the constants are significant in both Models 5 and 6 for Regimes 0 and 1, the alpha is only significant in Model 5's Regime 0 (α = 0.028803) and significant in both Regimes 0 and 1 for Model 6. However, no difference is shown between regimes because the coefficients for Model 6's alphas approach zero. Lastly, the beta value in Model 5's Regime 0 is significant (ß = 0.918535), as well as for Model 6's Regime 1 (ß = 1.00714).

The fact that the beta coefficients are very high compared to the coefficients for the other variables indicates the conditional variance to be significant. However, the fact that the beta coefficient is significant in Model 5's Regime 0 and Model 6's Regime 1 prevents a comparison.

While examining the transition probabilities, the probability of staying in the low volatility regime for BIST100 is 99% for both Models 3 and 4, just like the other indexes. If BIST100 is in the high volatility regime, the probability is 94% (Model 3) to 95% (Model 4) that it will stay in the same regime, or 6% (Model 3) to 5% (Model 4) that the regime switches to low volatility for the next observation.

Table 4. Equations, Probabilities, and Information Criteria for Models 5 and 6

Model 5: BIST100 1			**Model 6: BIST100 2**		
	Regime (0)	**Regime (1)**		**Regime (0)**	**Regime (1)**
ARMA Equation			**ARMA Equation**		
AR(1)	-0.843663 (0.133600)		AR(1)	0.560065 (0.233000)	0.352114 (0.142200)
AR(2)	0.046260 (0.122100)		AR(2)	-0.050662 (0.110800)	0.354522 (0.134900)
AR(3)	0.092741*** (0.091630)		AR(3)	0.095799*** (0.090000)	-0.516712 (0.143500)
MA(1)	0.841060*** (0.086990)		MA(1)	-0.542246 (0.219400)	-0.500733 (0.180600)
Constant	0.001806* (0.000658)	-0.006185* (0.003440)	Constant	0.005883* (0.003759)	-0.023158** (0.01185)
Variance Equation			**Variance Equation**		
Constant	0.001419* (0.001066)	0.000000** (0.013450)	Constant	0.006486* (0.001544)	0.000000* (0.007211)
Alpha	0.028803** (0.016020)	0.221972 (0.225700)	Alpha	0.000000** (0.032460)	0.000000*** (0.098270)
Beta	0.918535** (0.034850)	0.886515 (0.142000)	Beta	0.607445 (0.172500)	1.00714*** (0.067090)
Transition Probabilities			**Transition Probabilities**		
p_{0|0}	0.987417		p_{0|0}	0.987398	
p_{1|1}	0.943909		p_{1|1}	0.945289	
Information Criteria			**Information Criteria**		
log-likelihood 329.50747	AIC -5.393290	SC -5.062776	log-likelihood 330.992245	AIC -5.350295	SC -4.925345

Note: *, **, *** represent respectively 0.1, 0.05 and 0.01 significant levels.

The values in parenthesis represent standard errors.

Alpha and beta coefficients represent respectively ARCH and GARCH parameters.

Figure 6. Smoothed regime probabilities: Model 5.

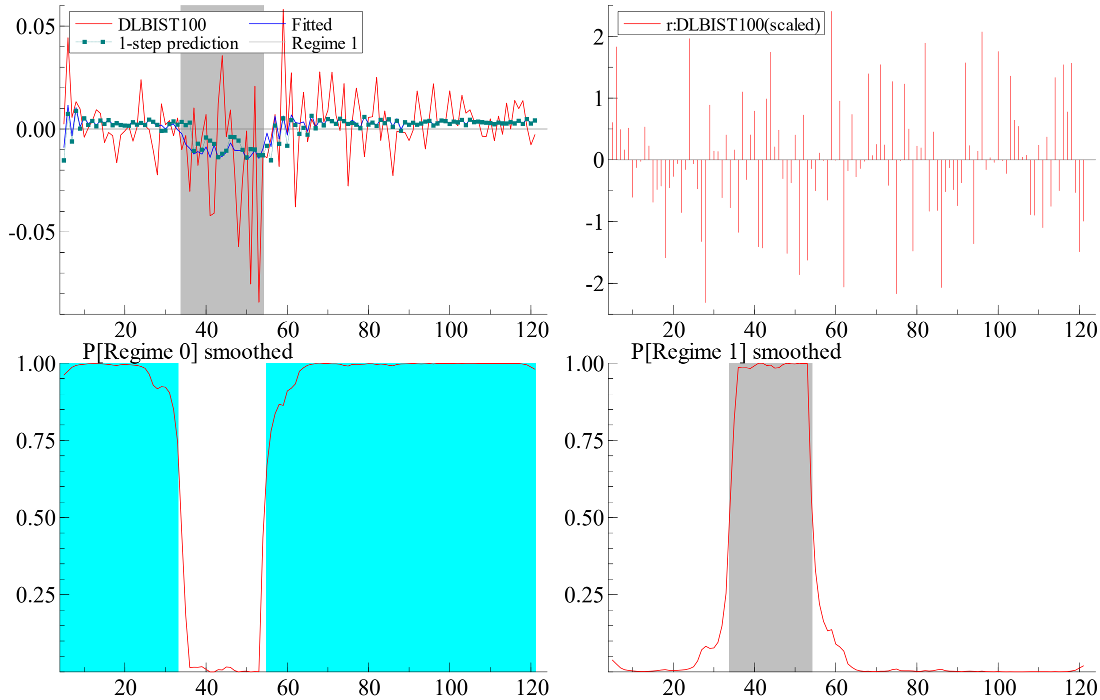
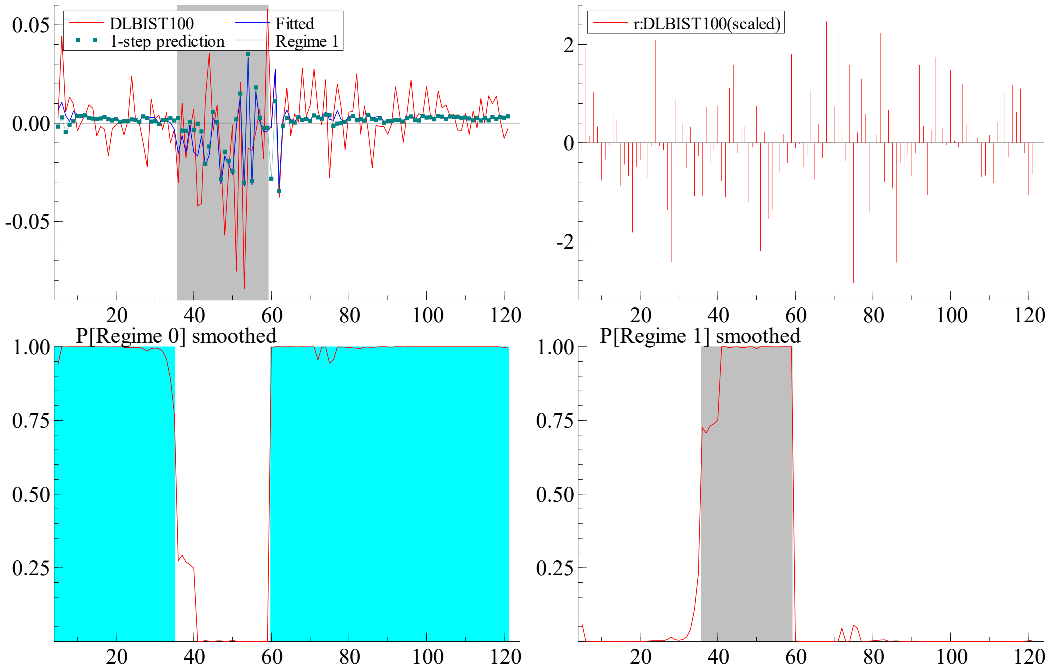


Figure 7. Smoothed regime probabilities: Model 6.



Empirical evidence from different models shows the Islamic index to have been stronger during the great collapse and recovery in the stock markets in the early stages of the COVID-19 pandemic. During periods of high volatility in particular, the losses for conventional indexes were 3-7 times higher than the gains in low volatility periods. However, the losses in the KATLM index during the high volatility period were two flows from the returns in the low volatility periods. The results provide evidence that investments in participation index stocks carry less risk during unstable or crisis periods.

4. Conclusion

The outbreak of COVID-19 has caused abrupt shocks in global markets, leading to fluctuations and crises in both the real and financial sectors due to disruptions in supply and demand. As a result, the Islamic financial sector, which has been gaining increasing attention in recent years, has also been affected by this crisis. However, some studies suggest that stock market indexes comprising financial instruments based on Sharia principles, with shares from companies adhering to these principles, may be more resilient to crises. Therefore, an empirical examination of the performance of these limited-size indexes during crises could serve as a useful guide for portfolio managers.

This study has examined the performances of the KATLM, BIST 30, and BIST 100 Indices from Borsa Istanbul during the fluctuations that occurred in the initial crisis period of the pandemic. For this purpose, the Markov regime-switching autoregressive moving average generalized autoregressive conditional heteroskedasticity (MS-ARMA-GARCH) model method has been used. Based on the principle of using daily data, the study examines the surge of COVID-19's impact on Turkey's markets from January 2 through June 25, 2020 using the Islamic participation indexes and the conventional BIST 100 and BIST 30 Indexes. We employed MS-ARMA-GARCH models with two regimes to investigate the low and high volatility regimes in the stock indexes. According to results obtained from our model, returns were observed to differ for all three indexes in the case of regime change. However, the changes occurring in BIST30, and BIST100 indexes were concluded to be higher than those for the KATLM index, with the losses in high volatility periods being nearly 4-7 times higher than the gains in low volatility periods in absolute values for BIST30, 3-4 times for BIST100, and 2 times for KATLM. These results provide evidence that the return fluctuations for BIST100 and BIST30 between different regimes is higher than those for KTLM.

Although all indexes under regime change have some losses, the participation index (KATLM) is seen to be more resistant than the conventional indexes in times of high volatility. These research results parallel those from studies presented in the literature (Abduh, 2017; Hkiri et al., 2017) and have determined that indexes based on Islamic principles are more resistant to crises. This study has a few limitations. We used restricted data for the initial pandemic period from one stock market and a single methodology for capturing return and volatility regimes. In future studies, examining a larger sample of conventional and Islamic stock indices from different markets is recommended using different methodologies.

References

ABDUH, Muhamad.; (2000), "Volatility of Malaysian Conventional and Islamic Indices: Does Financial Crisis Matter?", Journal of Islamic Accounting and Business Research.

AHMAD, Shabbir; ALSHARIF, Danyah.; (2019), "A Comparative Performance Evaluation of Islamic and Conventional Mutual Funds in Saudi Arabia", Munich, Germany: University Library of Munich.

AHMAD, Shabbir; ALSHARIF, Danyah.; (2019), "A Comparative Performance Evaluation of Islamic and Conventional Mutual Funds in Saudi Arabia".

ALAM, Mahfooz; ANSARI, Valeed Ahmad.; (2020), "Are Islamic Indices a Viable Investment Avenue? An Empirical Study of Islamic and Conventional Indices in India", International Journal of Islamic and Middle Eastern Finance and Management, 13.3: 503-518.

AL-AWADHI, Abdullah M., ALSAIFI, K., AL-AWADHI, A., & ALHAMMADI, S.; (2020), "Death and Contagious Infectious Diseases: Impact of the COVID-19 Virus on Stock Market Returns", Journal of behavioral and experimental finance, 27: 100326.

AL-KHAZALI, Osamah; LEAN, Hooi Hooi; SAMET, Anis.; (2014), "Do Islamic Stock Indexes Outperform Conventional Stock Indexes? A Stochastic Dominance Approach", Pacific-Basin Finance Journal, 28: 29-46.

ALOUİ, Chaker, HKİRİ, Besma, MARCO, Lau Chi Keung, & YAROVAYA, Larisa.; (2016), "Investors' Sentiment and US Islamic and Conventional Indexes Nexus: A Time–Frequency Analysis" ,Finance Research Letters, 19, 54–59.

ANDERSEN, Torben G., BOLLERSLEV, Tim, & DIEBOLD, Francis X.; (2003), "Modeling and Forecasting Realized Volatility" ,Econometrica, 71(2), 579–625.

ANDERSON, Heather M.; NAM, Kiseok; VAHID, Farshid.; (1999), "Asymmetric Nonlinear Smooth Transition GARCH Models", Nonlinear time series analysis of economic and financial data, 191-207.

ATA, H. Ali; BUĞAN, Mehmet Fatih.; (2015), "Comparison of the Performances Islamic and Conventional Market Indices and Their Causal Relationship", International Journal of Business Management and Economic Research (IJBMER), 6.6: 455-462.

BAILLIE, Richard T.; BOLLERSLEV, Tim; MIKKELSEN, Hans Ole.; (1996), "Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity", Journal of econometrics, 74.1: 3-30.

BAUER, Rob; KOEDIJK, Kees; OTTEN, Roger.; (2005), "International Evidence on Ethical Mutual Fund Performance and Investment Style", Journal of banking & finance, 29.7: 1751-1767.

BİLDİRİCİ, Melike E., AYKAÇ ALP, Elçin, ERSİN, Ö. Ö., & BOZOKLU, Ü.; (2010), " İktisatta Kullanılan Doğrusal Olmayan Zaman Serisi Yöntemleri ", Istanbul, Turkey: Türkmen Kitabevi.

BOLLERSLEV, Tim.; (1986), "Generalized Autoregressive Conditional Heteroskedasticity", Journal of econometrics, 31.3: 307-327.

BOSSMAN, A., JUNIOR, P. O., Tiwari, A. K. (2022), Dynamic connectedness and spillovers between Islamic and conventional stock markets: time- and frequency-domain approach in COVID-19 era. *Heliyon*, 8.

CAI, Jun.; (1994), "A Markov Model of Switching-Regime ARCH" , Journal of Business & Economic Statistics, 12.3: 309-316.

CHAPRA, M. Umer.; (2011), "The Global Financial Crisis: Can Islamic Finance Help?", Islamic Economics and Finance: A European Perspective, 135-142.

CHOWDHURY, M.I.H., BALLI, F. and de BRUIN, A. (2022), Islamic equity markets versus their conventional counterparts in the COVID-19 age: Reaction, resilience, and recovery. *International Review of Finance*, 22: 315-324.

DEWANDARU, Ginanjar, RIVZI, Syed Aun R., BACHA, Obiyathulla I., & MASIH, Mansur; (2014), "What Factors Explain Stock Market Retardation in Islamic Countries" , Emerging Markets Review, 19, 106–127.

DHARANI, M.; NARAYANAMOORTHY, Vijayakumar; NATARAJAN, P.; (2011), "A Study on the Performance of Islamic Index and the Common Index During Bull and Bear Market Period", Journal of Emerging Financial Markets, 2.1: 29-36.

DUEKER, Michael J.; (1997), "Markov Switching in GARCH Processes and Mean-Reverting Stock-Market Volatility", Journal of Business & Economic Statistics,15.1: 26-34.

ELFAKHANI, Said; HASSAN, M. Kabir; SIDANI, Yusuf.; (2005), "Comparative Performance of Islamic Versus Secular Mutual Funds", In: 12th economic research forum conference in Cairo, Egypt. p. 19-21.

ENGLE, Robert F.; (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation", Econometrica: Journal of the econometric society, 987-1007.

ENGLE, Robert F.; LILIEN, David M.; ROBINS, Russell P.; (1987), "Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model", Econometrica: journal of the Econometric Society, 391-407.

FORNARI, Fabio; MELE, Antonio.; (1997), "Sign-and Volatility-Switching ARCH Models: Theory and Applications to International Stock Markets", Journal of Applied Econometrics, 12.1: 49-65.

FRENCH, Kenneth R.; SCHWERT, G. William; STAMBAUGH, Robert F.; (1987), "Expected Stock Returns and Volatility", Journal of financial Economics, 19.1: 3-29.

FUN-HO Catherine Soke, RAHMAN Nurul Afiqah Abd, YUSUF, Noor Hafizha Muhamad, & ZAMZAMİN, Zaminor.; (2014), "Performance of Global Islamic Versus Conventional Share Indices: International Evidence" , Pacific-Basin Finance Journal, 28, 110–121.

GLOSTEN, Lawrence R.; JAGANNATHAN, Ravi; RUNKLE, David.; (1993), "On the Relation Between the Expected Value and the Volatility of the Nominal Excess Return on Stocks", The journal of finance, 48.5: 1779-1801.

GONZÁLEZ-RIVERA, Gloria.; (1998), "Smooth-Transition GARCH Models", Studies in Nonlinear Dynamics & Econometrics, 3.2.

GUNAY, Samet.; (2015), "Markov Regime Switching Generalized Autoregressive Conditional Heteroskedastic Model and Volatility Modeling for Oil Returns" , International Journal of Energy Economics and Policy, 5.4: 979-985.

HAKIM, Sam; RASHIDIAN, Manochehr.; (2004), "Risk and Return of Islamic Market Indexes", In: Makalah Seminar di Malaysia.

HAMILTON, James D., (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle", Econometrica: Journal of the econometric society, 357-384.

HAMILTON, James D.; SUSMEL, Raul.; (1994), "Autoregressive Conditional Heteroskedasticity and Changes in Regime", Journal of econometrics, 64.1-2: 307-333.

Hasan, M. B., Mahi, M., Hassan, M.K., Bhuiyan, A.B. (2021), Impact of COVID-19 pandemic on stock markets: Conventional vs. Islamic indices using wavelet-based multi-timescales analysis. *The North American Journal of Economics and Finance*, 58.

HASSAN, M. Kabir; GIRARD, Eric.; (2010), "Faith-Based Ethical Investing: The Case of Dow Jones Islamic Indexes", Islamic Economic Studies, 17.2.

HEYDEN, Kim J.; HEYDEN, Thomas.; (2021), "Market Reactions to the Arrival and Containment of COVID-19: an Event Study" , Finance research letters, 38: 101745.

HKIRI, Besma, HAMMOUDEH, Shawkat, ALOUI, Chaker, & YAROVAYA, Larisa.; (2017), "Are Islamic Indexes a Safe Haven for Investors? An Analysis of Total, Directional and Net Volatility Spillovers Between Conventional and Islamic Indexes and Importance of Crisis Periods", Pacific-Basin Finance Journal, 43, 124–150.

HO, Catherine Soke Fun, RAHMAN, Nurul Afiqah Abd, YUSUF, Noor Hafizha Muhamad, & ZAMZAMIN, Zaminor.; (2014), "Performance of Global Islamic Versus Conventional Share Indices: International Evidence", Pacific-Basin Finance Journal, 28, 110–121.

HOQUE, Hafiz, KABIR, Sarkar Humayun, ABDELBARI, El Khamlichi, & MANAHOV Victor.; (2016), "Islamic and Conventional Equity Market Movements During and After the Financial Crisis: Evidence from the Newly Launched MSCI Indices" , Financial Markets Institutions & Instruments, 25(4), 217–252.

HUSSEIN, Khaled A.; (2007), "Islamic Investment: Evidence from Dow Jones and FTSE Indices", Islamic Economics and Finance, 387.

JAWADI, Fredj; JAWADI, Nabila; LOUHICHI, Wael.; (2014), "Conventional and Islamic Stock Price Performance: An Empirical Investigation", International Economics, 137: 73-87.

KAYED, Rasem N.; HASSAN, M., Kabir.; (2011), "The Global Financial Crisis and Islamic Finance", Thunderbird International Business Review, 53.5: 551-564.

KIM, Chang-Jin.; (1993), "Unobserved-Component Time Series Models with Markov-Switching Heteroscedasticity: Changes in Regime and the Link Between Inflation Rates and Inflation Uncertainty", Journal of Business & Economic Statistics, 11.3: 341-349.

KLAASSEN F.; (1999), "Improving GARCH Volatility Forecasts" Unpublished manuscript, Tilburg University.

KROLZIG, Hans-Martin.; (2000), "Predicting Markov-switching Vector Autoregressive Processes", Oxford: Nuffield College.

MAJDOUB, Jihed; MANSOUR, Walid.; (2014), "Islamic Equity Market Integration and Volatility Spillover between Emerging and US Stock Markets" , The North American Journal of Economics and Finance, 29: 452-470.

MARCUCCI, Juri.; (2005), "Forecasting Stock Market Volatility with Regime-Switching GARCH Models", Studies in Nonlinear Dynamics & Econometrics, 9.4.

MINIAOUI, Hela, SAYANI, Hameedah, & CHAIBI, Anissa.; (2015), "The Impact of Financial Crisis on Islamic and Conventional Indices of the GCC Countries" , Journal of Applied Business Research, 31(2), 357–370.

NELSON, Daniel B.; (1990), "Stationarity and Persistence in the GARCH (1, 1) Model" , Econometric theory, 6.3: 318-334.

ONALI, Enrico.; (2020), "Covid-19 and Stock Market Volatility", Available at SSRN 3571453.

PORTEBA, James M., & SUMMERS, Lawrence H.; (1986), "The Persistence of Volatility and Stock Market Returns", American Economic Review, 76, 1142–1151.

RAMELLI, Stefano; WAGNER, Alexander F.; (2020), "Feverish Stock Price Reactions to COVID-19", The Review of Corporate Finance Studies, 9.3: 622-655.

RIZVI, Syed Aun R.; ARSHAD, Shaista.; (2018), "Understanding Time-Varying Systematic Risks in Islamic and Conventional Sectoral Indices", Economic Modelling, 70: 561-570.

SENTANA, Enrique.; (1995), "Quadratic ARCH Models", The Review of Economic Studies, 62.4: 639-661.

SEVEN, Ünal; YILMAZ, Fatih.; (2021), "World Equity Markets and COVID-19: Immediate Response and Recovery Prospects" , Research in International Business and Finance, 56: 101349.

SHAMSUDDIN, Abul.; (2014), “Are Dow Jones Islamic Equity Indices Exposed to Interest Rate Risk?”, Economic Modelling, 39: 273-281.

SMOLO, E., JAHANGIR, R., NAGAYEV, R., & TARAZI, C. S. C. (2022). Performances of Islamic and conventional equities during the global health crisis: Time-frequency analysis of BRICS+T markets. *Review of Financial Economics*, 40, 259– 280.

TAYLOR, Stephen J.; (2008), “Modelling Financial Time series”, World scientific.

TÜKENMEZ, Nevser Mine; ŞAKA, Hasan; KIZGIN, Merve.; (2019), “Conventional and Islamic Indices: A Comparison on Performance”, Muhasebe ve Finansman Dergisi, 2019.

WALKSHÄUSL, Christian; LOBE, Sebastian.; (2012), “Islamic Investing”, Review of Financial Economics, 21.2: 53-62.

World Bank, (2021), “Global Economic Prospects, January 2021”, Washington, DC: World Bank. doi: 10.1596/978-1-4648-1612-3.

ZAKOIAN, Jean-Michel.; (1994), “Threshold Heteroskedastic Models”, Journal of Economic Dynamics and control, 18.5: 931-955.

ZHANG, Dayong; HU, Min; JI, Qiang.; (2020), “Financial Markets Under the Global Pandemic of COVID-19”, Finance research letters, 36: 101528.

Appendix 1

Table: Unit Root Tests

		ADF			Philips Perron			KPSS	
		T-stat.	**Prob.**	**Lag**	**Bandwidth**	**Adj. T-stat.**	**Prob.**	**Bandwidth**	**L-M Stat.**
Katilim	I(0)	-1.725992	0.4156	2	6	-1.311775	0.6226	9	0.227679
	I(1)	-4.887282	0.0001	1	5	-8.276223	0.0000	6	0.151655
BIST30	I(0)	-1.167480	0.6868	2	5	-1.291488	0.6320	9	0.594855

	I(1)	-6.192546	0.0000	1	5	-11.19986	0.0000	4	0.298793
BIST100	I(0)	-1.160174	0.6898	2	5	-1.232421	0.6588	9	0.463595
	I(1)	-5.979522	0.0000	1	5	-10.99261	0.0000	5	0.277095

Notes: I(0): Natural logarithm and I(1): Natural logarithmic differences. Lag length is determined according to the Akaike information criterion. Maximum lags are determined "2". *, ** and *** respectively, 0.10, 0.05, and 0.01 indicates the level of statistical significance.

Appendix 2

Table: Selecting ARMA model

	ARMA	**AIC**
Katilim	(2, 0)	-4.976906
BIST30	(3, 1)	-5.039735
BIST100	(3, 1)	-5.046191