# Were Islamic Indices Resistant to Volatility During the COVID-19 Period?

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## Abstract

**Purpose : We examined the volatility and dependency structure between the Islamic and conventional indices throughout the crisis in this study.**

**Design/Methodology/Approach : The study used a dataset to analyze Islamic performance and its parent indices. By employing the GARCH model, we analyzed the volatility and dependency of the Copula model from January 1, 2017 to December 31, 2022. This period was subdivided into pre-COVID-19 and COVID-19 periods.**

**Findings : The findings showed that the COVID-19 pandemic has harmed the financial sector, affected stock prices, and increased volatility in Indian stock markets. The GARCH results demonstrated that AR and MA had positive coefficients in all the markets. The market is resilient to stock market shocks, as indicated by the significance of coefficients α and β. The dependency pattern in the post-COVID-19 cycle 2 was nearly identical as it was in the pre-COVID-19 for the majority of market sets. It showed that one market is dependent on another market.**

**Research Limitations/Implications : The crisis did not influence the Islamic market. This study was limited to a few stock indices. The study could be expanded by adding global markets with more significant time durations. We used GARCH and Copula in this study; Wavelet and DCC-GARCH models will be used in further studies. Finally, it will be helpful for investors to make investment decisions related to portfolio diversification and create awareness among investors.**

**Originality/Value : The study used econometric tools to examine dependency and volatility among the indices. It also analyzed whether Islamic indices performed better than their parent indices. A global framework with worldwide data was presented in this research. This could be accomplished using a worldwide analysis to avoid country-specific impacts.**

***Keywords :*** **Shariah indices, copula, COVID-19 pandemic, volatility spillover**

**JEL Classification Codes : G10, G11, G15**

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Crisis periods reveal how swift risks from extreme events can propagate across stock markets and sectors (Kumar et al., 2020; Wu et al., 2019). Islamic finance refers to a type of lending that conforms to Sharia law (Islamic law). This term also applies to investments following Islamic legal principles. With the

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expansion of Islam, Islamic finance and capital markets have become increasingly prevalent. The Shariah indices have been a significant factor in the recent expansion of the Islamic finance market. These are designed to bring investor rewards while abiding by Shariah. The first half of 2017 saw spectacular capital market expansion. It has grown from $200 billion in 2003 to a projected $4 trillion by 2030 (Alam & Seifzadeh, 2020).

The reason for conducting this study mainly stems from observing the dependency structure and volatility between Islamic and conventional indices. This rationale describes the remarkable variations in the Shariah and conventional indices using reorganized data and statistics throughout the turbulent COVID-19 pandemic. The GARCH (1,1) model is used in this study to examine volatility, whereas the copula model is employed to examine dependency. Additionally, empirical studies show that Shariah items do not provide a buffer during crises (Ajmi et al., 2014; Hammoudeh et al., 2014; Hassan et al., 2021; Sensoy, 2016; Shahzad et al., 2017). As per our knowledge, this study is the foremost that has used the GARCH and Copula modeling on Shariah and conventional indices, namely, S&P Africa Frontier (AFI), S&P Africa Frontier Shariah (AFSI), S&P Asia Pan (AI), S&P Asia Pan Shariah (ASI), S&P Europe 350 (EI350), and S&P Europe 350 Shariah (ESI350).

This study examines the unpredictability pattern and dependence structure of Islam and its parent indices by covering the period from January 2017 to December 2022 using the GARCH and Copula methods. The findings indicate that the COVID-19 outbreak impacted stock prices, increased volatility in Indian stock markets, and harmed the financial system. In post-COVID-19, $\alpha$ and $\beta$ both are positive, which shows the presence of volatility in the market, and the positive value of the asymmetric term shows that pessimistic shocks have a more substantial effect than optimistic shocks. The results of the GARCH analysis are also significant at the 1% significance level, meaning that negative news has a greater impact than positive news. The results also suggest that parent indices are more volatile than Islamic indices. In the pre-COVID-19 period, the dependency structure is symmetrical for approximately all market sets compared to the post-COVID-19 cycle 2. Over the usual period, it shows asymmetric patterns (upper-tail dependency) for all other time durations. In the post-COVID-19 cycle 2 period, the dependence structure is roughly symmetrical for all market pairs compared with the pre-COVID-19 period. The tail reliance between the Shariah indices and their parent indices has been more significant in the post-COVID-19 cycle two than in the other periods. This study focuses on the contribution of the Shariah indices to economic growth. It shows the results in terms of volatility and dependency, which will be helpful for investors and policymakers by including the Shariah indices in their portfolios to minimize risk.

## Literature Review

Siddiqui and Sumbul (2023) examined the performances of Islamic indices as well as conventional indices. They utilized data from two years for the Nifty 50 and Nifty 500, and their respective underlying assets and found their dependency during the pandemic. They used econometric tools such as correlation, GMM, cointegration, etc. The study determined that Islamic indices had a lower risk than conventional indices during crises, so it was safe to invest in them.

Comparison of volatility (i.e., risk) levels between traditional and Shariah indices for selected ASEAN and GCC countries after the COVID-19 pandemic (February 4 to June) was examined in 2020 (Sundarasen et al., 2023). Morlet's wavelet approach was used for this study. A comparable time frame of relative serenity, from February 4 to June 19, 2019, was chosen as a benchmark. Two findings were drawn from the analysis. The majority of Shariah indices were more volatile during the epidemic than their conventional equivalents. The Shariah and conventional indexes, however, seemed to be more alike in the GCC index pairings.

Khan et al. (2023) examined the dynamic relationship between Islamic stocks, oil, global policy uncertainty, and gold prices. From 1996M1 to 2018M12, we analyzed monthly data for the oil prices, Dow Jones World Islamic Stock Index, and global policy uncertainty using various wavelet coherence methods and co-integration.

The study's findings demonstrated bi-directional solid Granger causality between the original and discretized series variables. Polat et al. (2023) analyzed how the COVID-19 media coverage index (MCI) impacted the risk and volatility connections among five MSCI climate change indices: Europe, America, Japan, Emerging Markets, and Asia. It used four pandemic waves to segment the sample period from March 11, 2020, to January 19, 2022, and employed both frequency-dependent connectivity techniques and the TVP-VAR model. The findings indicated that most MSCI climate change indices acted as net transmitters of volatility, reflecting the pandemic's impact and that return shocks spread quickly, often within a week.

Tien and Hung (2022) examined the correlations between oil price volatility and stock indices in six of the Gulf Cooperation Council's (GCC) countries: Kuwait, the United Arab Emirates, Saudi Arabia, Oman, Qatar, and Bahrain. Maximum overlap discrete wavelet transform method filters were used with bivariate VARMA–GARCH–ADCC models to examine a wide range of potential spillover effects on the mean and variance of level prices over different time horizons from 2008 to 2019. Investors, portfolio managers, and other market participants should be aware of the significant correlation between oil prices and each stock market in the GCC countries. The study concluded that it can be used to develop optimal oil-GCC stock portfolios and to forecast volatility spillover patterns when developing hedging strategies more accurately.

Bahloul et al. (2022) analyzed the TSE 300 total return index's performance as traditional (non-SRI) and 24 Canadian SRI mutual fund investments during two separate periods: January 1990 to December 1999 and January 1995 to December 1999 (a five-year interval and a period of 10 years). They found no statistically significant difference in financial performance between SRI mutual funds and conventional funds. Nevertheless, it did show that the screened funds might have lower risk exposure**.** Adekoya et al. (2022) explored how the COVID-19 incidence influenced speculative and sentimental factors and examined the dynamic connectivity between conventional and Islamic stocks by sector during the pandemic. The findings highlighted the strong integration and competitiveness between these stock markets, with a total connectedness score of 93.7% and significant spillover effects. The dynamic portfolio analysis revealed that investments in conventional basic commodities, financial services, industrials, and oil and gas stocks reduced portfolio volatility while other investments increased it.

Ashraf et al. (2022) examined whether investing in Islamic equity provided investors with any hedging advantages during the COVID-19 epidemic compared to the pre-COVID-19 period. The authors contended that IEIs offered hedging advantages by delivering positive excess returns without raising systematic risk during extremely unfavorable market situations, such as the COVID-19 pandemic. MVE-based IEIs exhibited more pronounced hedging benefits than IEIs produced with BVTA-based Shariah screening criteria. IEIs also offered excess performance under normal market conditions, typically accompanied by higher systematic risk, indicating that a more extensive, non-diversifiable risk accompanied the extra performance. Mzoughi et al. (2022) examined the impact of COVID-19 on markets across six regions: North America, Latin America, Europe, the Pacific, the Gulf Cooperation Council, and Asia. They found that a portfolio that included Islamic and gold indexes performed best over the two periods, reinforcing gold's role as a haven. Additionally, portfolios with Brent and conventional or Islamic indexes showed similar performance.

Aloui et al. (2022), in light of the ongoing COVID-19, examined the connections between Chinese Islamic and conventional stocks. The study aimed to determine how much the COVID-19 uncertainty and related pronouncements affected the relationship between Islamic stocks and their conventional stocks. During the pandemic, the MGARCH, as specified by the DCC, showed a notable pattern of time-varying dependence between conventional and Islamic stocks. Given the impact of pandemic computation, we think that pandemic fatalities had a major impact on large-cap stocks, and pandemic-infected cases added to the association. The number of patients who recovered, however, did not affect the magnitude of DCC. From a financial perspective,

this finding suggests that the degree of dependence of Islamic large-cap stocks on their conventional stocks was influenced by "bad news" about contamination instances and deaths.

Ali et al. (2021) examined that sukuk returns were positive ; whereas, conventional bond returns indicated a negative trend, according to research comparing the effects of conventional and Islamic bonds. The market dynamics had a greater impact on conventional returns, which led to the conclusion that Islamic financing was necessary for investors to reduce risk at the ideal level. Ahmad and Ibrahim (2002) compared the three-year performance of the KLSI and KLCI indices by analyzing their risk and return using methods such as the adjusted Sharpe ratio, *t*-test, adjusted Jensen Alpha, and Treynor Index. The sample was divided into periods: the entire period, a growth period (April 1999 to February 2000), and a decline period (March 2000 to January 2002). The results showed that while the KLSI had lower returns overall and during the decline, it slightly outperformed the KLCI during the growth period.

Trabelsi et al. (2020) compared the performance of traditional and Islamic indices to determine their level of heterogeneity. Using the Markov regime-switching model, the maximum Sharpe ratio algorithm, and the Sharpe ratio difference test, the analysis focused on the closing prices of MSCI Islamic stock indices and their conventional US counterparts. The results showed that Islamic indices performed better than conventional and mixed portfolios. Investors choosing Islamic indices will not perform worse than those selecting conventional ones. Singha et al. (2024) investigated structural breakpoints and the causal relationship between spot and futures markets for 12 commodities traded in India. The Multi Commodity Exchange (MCX) data included agricultural, energy, precious metals, and base metals commodities. Structural breaks were identified using a multiple breakpoint test, segmenting price series into sub-periods. Within a vector autoregressive (VAR) framework, the Granger causality test was applied to examine these relationships over the entire period and within sub-periods. Bidirectional causality, indicating market efficiency, was found across all commodities for the full period. However, certain sub-periods showed unidirectional causality, suggesting market inefficiencies due to political or economic events.

Given the direct influence of oil prices on inflation, Vijayakumar and Karthikeyan (2024) examined the impact of global GDP and inflation on crude oil price volatility. Using bivariate GARCH models (diagonal VEC GARCH and BEKK GARCH), the analysis covered data from January 2000 to December 2022 to explore the volatility and spillover effects among global GDP, inflation, and crude oil prices. The findings revealed significant conditional correlations between global GDP and crude oil prices, indicating a mutual relationship with volatility spillover in their co-variance. However, global GDP and inflation did not exhibit volatility spillover effects on crude oil prices. A strong correlation was identified between global inflation rates and crude oil prices, though global GDP showed an insignificant and reverse impact on crude oil price changes. Additionally, the study found that volatility in the global inflation rate negatively influenced crude oil prices through spillover effects.

Kaura et al. (2019) examined the dynamics between futures and spot markets for key agricultural commodities in India, specifically crude palm oil, cardamom, mentha oil, and cotton traded on the MCX. The research examined the speed, magnitude, and significance of error correction in the presence of arbitrage opportunities and investigated the causality relationship between the futures and spot markets. They underscored the importance of futures markets in maintaining price stability and providing market participants with tools to mitigate risks associated with price fluctuations in agricultural commodities. Vodwal and Vodwal (2024) investigated the asymmetric impact of COVID-19 lockdowns and social distancing measures on the performance and short-term financing of Indian manufacturing and services industries. By analyzing these sectors independently, the study aimed to diagnose the varied effects of COVID-19 regulations and the influence of exogenous shocks on the determinants of the short-term debt ratio. The findings confirmed that the pandemic negatively and unevenly affected Indian industries, with manufacturing performance dropping by 69% and services by 91%. The short-term debt ratio also declined significantly, with a slight decrease of 0.0204 in manufacturing and a reduction of

0.0244 in services. The study highlighted substantial deviations in the determinants of the short-term debt ratio: profit, size, and liquidity were key factors for manufacturing firms, while liquidity was the sole determinant for service sector firms.

Sachdeva et al. (2023) evaluated the corporate social responsibility (CSR) activities of financial corporations in India, focusing on banks and non-banking financial companies (NBFCs). Using content analysis, the CSR performance of 63 financial institutions listed on the NSE starting from session 2014 ending in 2021 was quantified. Financial institutions have a big social responsibility since they lend loan money using assets from savings account holders. The research employed descriptive statistics, Cronbach's alpha, and *z*-score tests to assess the accuracy and consistency of the CSR scores. The findings indicated that private sector banks were more proactive in CSR activities than public sector banks and NBFCs. Additionally, CSR scores showed improvement over the study period.

Behal and Uppal (2023) studied the factors influencing CSR disclosure among top Indian firms across selected industrial sectors. The study aimed to identify significant determinants of CSR disclosure using both variables on finance. Data were sourced from CSR reports, annual reports, other public sources, and company websites, using fixed-effect regression on 708 observations starting from 2014 and ending in 2019. Four regression models were developed to test the impact of institutional ownership, promoters' ownership, innovation on CSR disclosure, and company popularity. The findings indicated that age, firm size, and leverage were strong positive determinants of CSR reporting. Conversely, promoters' ownership showed a weak negative effect, while profitability had no significant impact on CSR scores. Institutional ownership and innovation were also insignificant determinants of CSR disclosure.

Joseph et al. (2023) explored the scoping review, investigated the existing literature on FinTech's impact on financial competence, and concluded the analyzed data. Danielle Levac's recommendations and using the Arksey and O'Malley scoping review framework, the study identified and analyzed 246 papers from major databases, ultimately selecting 54 relevant studies through a rigorous screening process. Independent data coding and inclusion/exclusion screening were conducted. The review revealed that research on FinTech and financial competence began in 2012, with a significant increase in studies starting in 2020. The analysis highlighted financial inclusion as the primary focus of major FinTech studies, indicating potential research gaps in other areas of economic competence. Based on these findings, recommendations and future research directions in this emerging field are suggested.

Patel et al. (2023) examined the combination between the markets of MSCI Emerging Markets and the USA, focusing on the period surrounding the 2008 financial crisis. Short-term integration was assessed using Granger causality and correlation tests, while long-term integration was analyzed using the VAR and ADF tests. The findings revealed that bond markets became more interconnected post-crisis, but overall market integration remained limited, providing opportunities for portfolio diversification. The global financial crisis of 2008 increased the integration between MSCI's Emerging Asian markets as well as the United States market. VAR and impulse response analyses indicated that inventions in the US and Chinese markets had the most significant impact on the Indian market, while other markets had minimal influence.

## Methodology

The study is completely based on the secondary data collected from www.s&pglobal.com, covering six years from January 1, 2017 to December 31, 2022. The data have been divided into five periods before COVID (January 1, 2017 to December 31, 2022), during the COVID cycle 1 (January 1, 2020 to November 30, 2020), post-COVID cycle 1 (December 1, 2020 to March 31, 2021), during COVID cycle 2 (January 1, 2021 to June 30, 2021), and post-COVID cycle 2 (July 1, 2021 to December 30, 2022) by taking the S&P Africa Frontier

(AFI), S&P Africa Frontier Shariah (AFSI), S&P Asia Pan (AI), S&P Asia Pan Shariah (ASI), S&P Europe 350 (EI350), and S&P Europe 350 Shariah (ESI350) indices. We collected data from S&P because it has a huge collection of indices and covers the specific time duration of the COVID-19 pandemic. Three years prior to the pandemic and three years during the pandemic, we took six years of data for proper and accurate results. The software which is used in the study is E-views and R.

We show the descriptive statistics of day-to-day returns of Shariah's and their parent indices. We calculate the day-to-day yields based on the subsequent log function:

$Rt = \mathrm{LN}(Pt/P(t-1))$.

*Rt* and *Pt* denote the day-to-day returns of the day *t*.

### *Descriptive Statistics*

The pre-COVID-19 analysis is shown in Table 1; ASI has the highest return (0.02409) compared to another variable with the highest volatility. AFSI shows the least return (–0.00204). When the AFSI displays zero skewness, it means that it is normally distributed, all other indices are shown skewed left or the left tail is long. AFSI, AI, ASI, EI350, and ESI350 are shown in the normal quartile except one quartile AFI, which shows positive kurtosis or right tail. Islamic indices get maximum return before the crisis.

Table 2 shows descriptive statistics for COVID-19 phase 1, showing that the Shariah index ASI (0.044298) yields the highest returns when compared to other traditional and Shariah indices. Skew shows a negatively skewed left, which means lengthening the left tail relative to the right tail. There are no quartiles between the indices in this series; they are all closely spaced together. EI350 has the highest standard deviation (0.800085), whereas AFI has the lowest (0.050823).

**Table 1.** ***Descriptive Statistics of Pre-COVID-19 Time Period***

| | AFI | AFSI | AI | ASI | EI350 | ESI350 |
|---|---|---|---|---|---|---|
| Mean | 0.001341 | –0.00204 | 0.01246 | 0.02409 | 0.007039 | 0.015944 |
| Median | 0.002597 | –0.00243 | 0.024597 | 0.031541 | 0.018612 | 0.023898 |
| Standard Deviation | 0.269576 | 0.368294 | 0.28449 | 0.396662 | 0.29648 | 0.298271 |
| Skewness | –1.15765 | 0.087625 | –0.66893 | –0.27622 | –0.33401 | –0.30873 |
| Kurtosis | 18.55039 | 6.400151 | 5.893961 | 4.223091 | 4.989355 | 4.464509 |
| Jarque–Bera | 8043.497 | 377.2146 | 330.7813 | 58.61229 | 143.3065 | 82.20151 |
| Maximum | 1.185475 | 1.925281 | 0.90251 | 1.510414 | 1.200025 | 1.109385 |

**Table 2.** ***Descriptive Statistics During COVID-19 Cycle 1***

| | AFI | AFSI | AI | ASI | EI350 | ESI350 |
|---|---|---|---|---|---|---|
| Mean | –0.02436 | –0.00264 | 0.018956 | 0.044298 | –0.01587 | 0.002943 |
| Median | –0.00512 | –0.00263 | 0.082749 | 0.066481 | 0.023559 | 0.047743 |
| Standard Deviation | 0.50823 | 0.539985 | 0.559647 | 0.691212 | 0.800085 | 0.678516 |
| Skewness | –1.69465 | –1.09401 | –0.42679 | –0.39278 | –1.42301 | –1.31042 |
| Kurtosis | 10.77893 | 9.283011 | 6.776167 | 5.199756 | 13.10115 | 11.25789 |
| Jarque–Bera | 713.9904 | 438.9479 | 148.6315 | 54.10572 | 1092.153 | 744.3603 |
| Maximum | 1.226916 | 1.519739 | 2.359533 | 2.721785 | 3.539756 | 2.794039 |

**Table 3.** ***Descriptive Statistics of Post-COVID-19 Cycle 1***

| | AFI | AFSI | AI | ASI | EI350 | ESI350 |
|---|---|---|---|---|---|---|
| Mean | 0.004325 | 0.038756 | 0.033512 | 0.033736 | 0.046342 | 0.031733 |
| Median | 0.014644 | –0.00222 | 0.039065 | 0.046202 | 0.055872 | 0.035666 |
| Standard Deviation | 0.27377 | 0.433837 | 0.415376 | 0.601669 | 0.320669 | 0.322263 |
| Skewness | –0.2981 | 0.734149 | –0.85693 | –0.04635 | –0.41996 | –0.14043 |
| Kurtosis | 4.321588 | 3.902259 | 4.407462 | 3.040527 | 4.635479 | 3.519341 |
| Jarque–Bera | 7.532356 | 10.64239 | 17.62388 | 0.03668 | 12.11256 | 1.249137 |
| Maximum | 0.727279 | 1.397249 | 0.814864 | 1.49529 | 0.916886 | 0.848158 |

**Table 4.** ***Descriptive Statistics During COVID-19 Cycle 2***

| | AFI | AFSI | AI | ASI | EI350 | ESI350 |
|---|---|---|---|---|---|---|
| Mean | 0.050242 | 0.058926 | 0.01182 | –0.01273 | 0.031931 | 0.050432 |
| Median | 0.05597 | 0.007767 | 0.039591 | –0.00981 | 0.062191 | 0.070969 |
| Standard Deviation | 0.170433 | 0.409777 | 0.291834 | 0.36871 | 0.303717 | 0.308069 |
| Skewness | –0.11684 | 0.69012 | –0.5482 | –0.36104 | –0.88732 | –0.42986 |
| Kurtosis | 4.301497 | 3.975979 | 4.05981 | 4.705129 | 4.969965 | 3.644371 |
| Jarque–Bera | 4.662661 | 7.62026 | 6.200726 | 9.143611 | 18.74688 | 3.078189 |
| Maximum | 0.520061 | 1.366847 | 0.764156 | 0.826166 | 0.81688 | 0.7536 |

**Table 5.** ***Descriptive Statistics of Post-COVID-19 Cycle 2***

| | AFI | AFSI | AI | ASI | EI350 | ESI350 |
|---|---|---|---|---|---|---|
| Mean | –0.01392 | –0.04005 | –0.02998 | –0.0504 | –0.0059 | –0.01008 |
| Median | –0.00942 | –0.03519 | –0.03254 | –0.07957 | 0.024212 | 0.015258 |
| Standard Deviation | 0.210922 | 0.419948 | 0.431035 | 0.637135 | 0.459976 | 0.470955 |
| Skewness | 0.060693 | 0.159329 | 0.247322 | 0.82961 | –0.22028 | –0.04481 |
| Kurtosis | 4.027927 | 4.076159 | 4.275015 | 6.792081 | 4.816263 | 4.302452 |
| Jarque–Bera | 17.45436 | 20.52198 | 30.47088 | 279.1233 | 56.90521 | 27.76774 |
| Maximum | 0.752191 | 1.619946 | 1.989483 | 3.647221 | 1.94596 | 1.795706 |

The post-COVID-19 phase 1 research is referenced in Table 3. The series demonstrates how the Shariah indices have increased quickly and outperformed conventional indices globally. AFSI displays the lowest return (–0.00204). All other indices are demonstrated to be skewed to the left or to have lengthy left tails; however, the AFSI exhibits zero skewness, indicating that it is regularly distributed. Except for one quartile, AFI, the other quartiles of the AFSI, AI, ASI, EI350, and ESI350 are displayed as regular quartiles. In the post-Covid-19 phase 1 era, Islamic indices had higher volatility than traditional indices.

Table 4 shows the maximum returns in Shariah indices such as AFSI (0.058926) and EI350 (0.050432) during COVID-19 phase 2; however, one index gets low ASI (–0.01273) instead of conventional indices like AFI, EI, whereas AI generates higher returns. Except for AFSI, all other indices are normally distributed. All this has left skewed long tails. They are not even close yet.

The post-COVID-19 phase 2 research, Shariah market extreme volatility indices, is discussed in Table 5. The capital market crisis is not affected by Shariah indices, while the traditional markets get the effects of COVID-19.

They get the lowest return of AFI, AI, and EI350 as compared to AFSI, ASI, and ESI350. The peak of outliers is highest for the ASI distribution, followed by the others, respectively, and is correlated with increased kurtosis.

## GARCH Modeling

GARCH models become essential in time series data analysis, notably in financial analysis, where the objective is to assess and forecast volatility. Engle (1982) discovered that while many financial time series, including stock returns and exchange rates, are unexpected, there is a visible clustering in variance or volatility. This phenomenon is referred to as conditional heteroskedasticity; although the series is stable overall, the conditional calculated return of the variance may be time-dependent. This marginal model is based on the traditional GARCH model, with the standard innovation following the normal distribution (Equation 1).

$$ht+1=\omega+\alpha\varepsilon t2+\beta ht \qquad \ldots\ldots.(1)$$

Figure 1 represents the plotted returns; the last quarter of 2017, in the case of the African markets, shows higher volatility due to the food crisis in the country. Again, the initial quarters of the year 2020 approved the higher volatility in all indices, i.e., Shariah and their underlying. It can also be observed that the Islamic markets are extra

**Figure 1.** ***Volatility Clustering During Pre-COVID-19 Period***

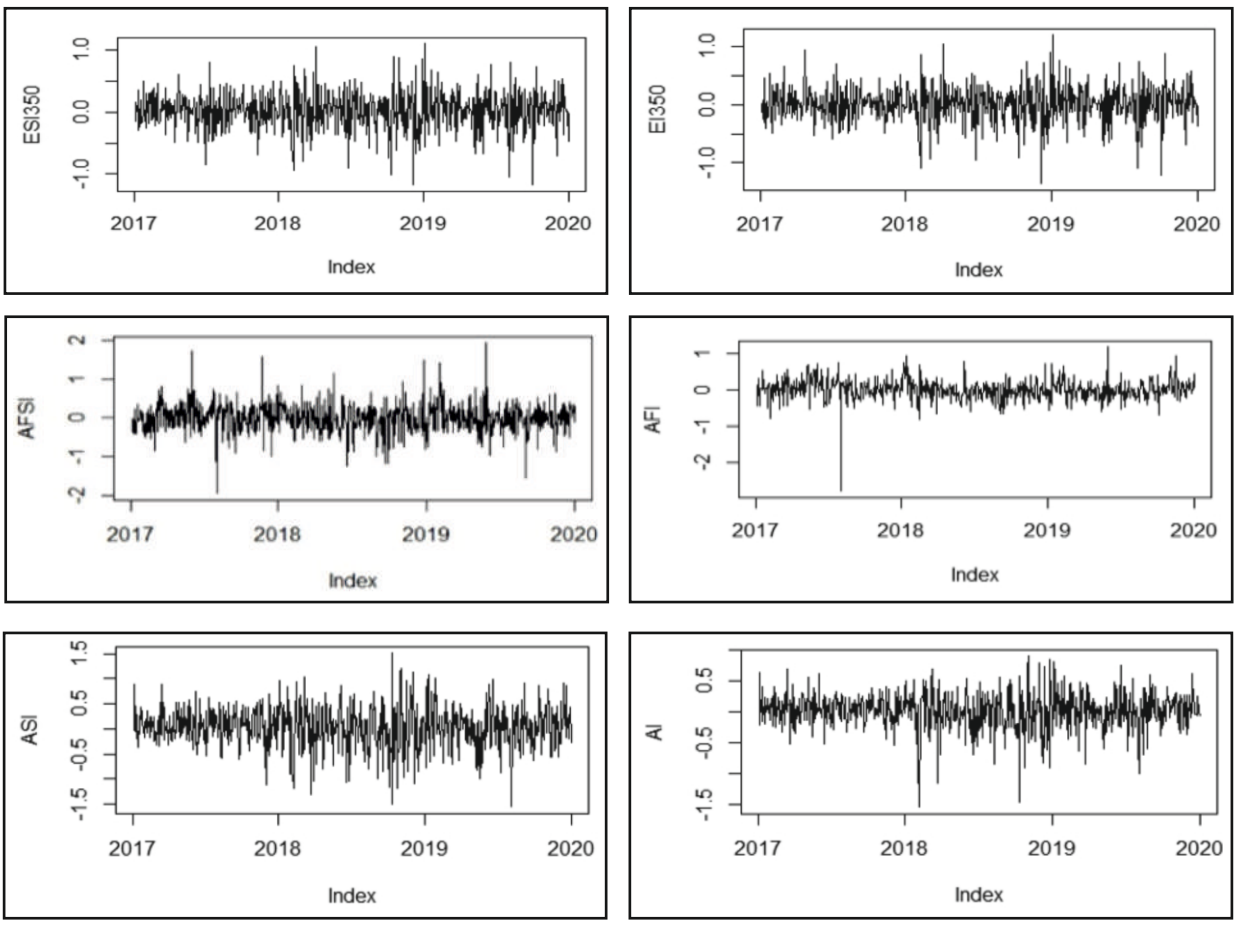

**Table 6.** ***GARCH (1,1) of Pre-COVID-19 Time Period***

| | AI | ASI | AFI | AFSI | EI350 | ESI30 |
|---|---|---|---|---|---|---|
| μ | 0.027124 | 0.042622 | 0.000894 | – 0.002026 | 0.024315 | 0.029379 |
| | (0.003289) | (0.000962) | (0.92303) | (0.877805) | (0.010715) | (0.001878) |
| Ω | 0.001692 | 0.003040 | 0.042559 | 0.001544 | 0.008944 | 0.007790 |
| | (0.088380) | (0.095074) | (0.00000) | (0.020375) | (0.004331) | (0.006871) |
| α | 0.070737 | 0.062411 | 0.309653 | 0.00000 | 0.151346 | 0.143686 |
| | (0.000413) | (0.000733) | (0.00000) | (0.999999) | (0.000027) | (0.000020) |
| β | 0.909600 | 0.919299 | 0.115898 | 0.988848 | 0.753555 | 0.773732 |
| | (0.000000) | (0.000000) | (0.31378) | (0.00000) | (0.0000000) | (0.00000) |

volatile as equated to their underlying indices due to the COVID-19 pandemic in the economy. Additionally, we apply the GARCH model (1,1) for estimating the returns and the results are shown in Table 6; according to the results of the GARCH analysis, the coefficients of MA and AR are positive, which represents that current returns depend on the previous returns. The α and β terms are significant at a 1% level of significance, which means that the shocks are persistent.

Figure 2 shows the results of COVID-19 Cycle 1. All markets were extremely volatile during COVID-19

**Figure 2.** ***Volatility Clustering During COVID-19 Cycle 1***

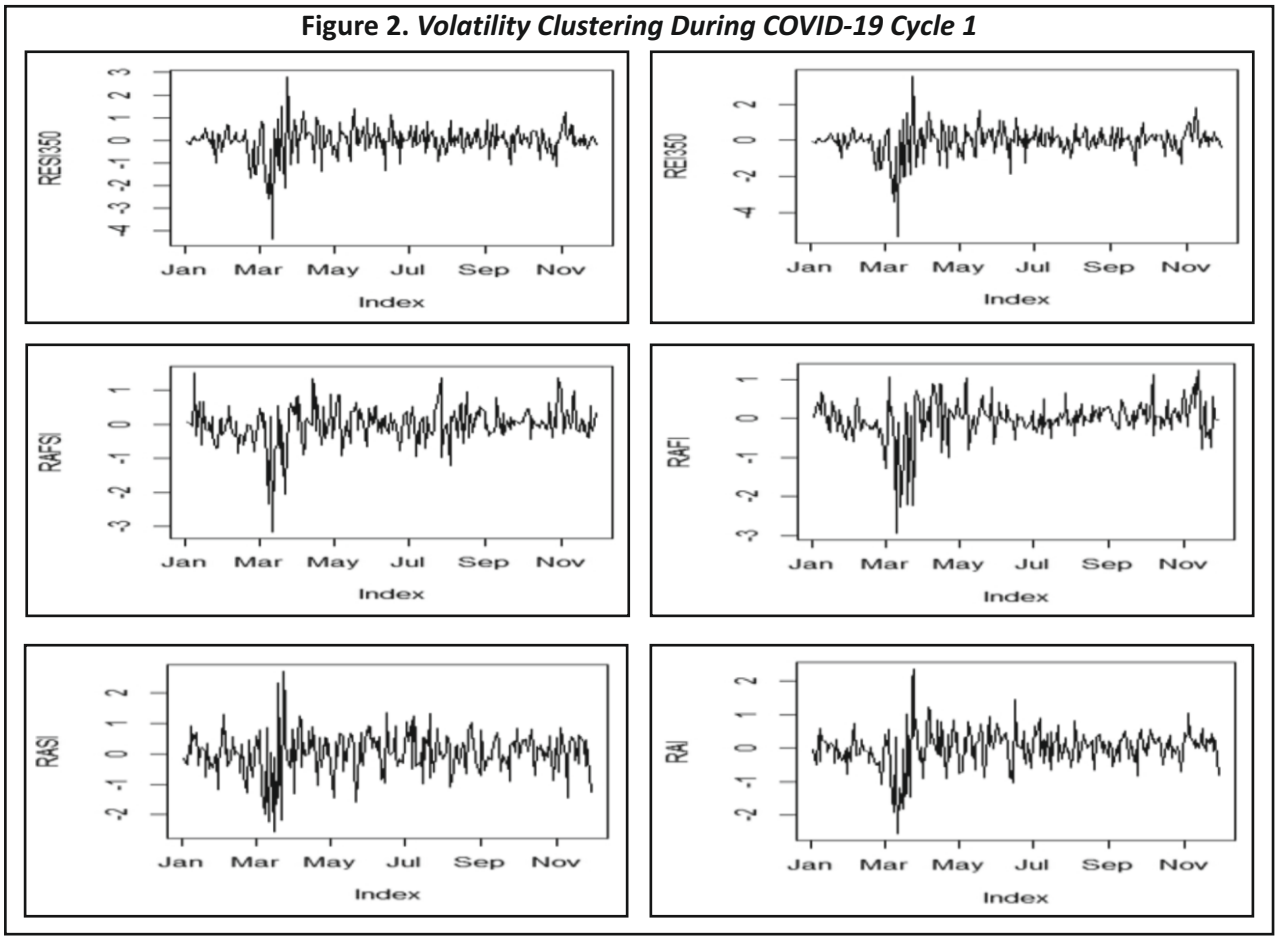

**Table 7.** ***GARCH (1,1) of During COVID-19 Cycle 1***

| | AI | ASI | AFI | AFSI | EI350 | ESI30 |
|---|---|---|---|---|---|---|
| μ | 0.032229 | 0.050378 | 0.021880 | 0.026370 | 0.026233 | 0.027715 |
| | (0.249398) | (0.198270) | (0.3783842) | (0.426501) | (0.430044) | (0.396020) |
| Ω | 0.020421 | 0.058221 | 0.009825 | 0.018743 | 0.018489 | 0.030454 |
| | (0.066198) | (0.089111) | (0.108395) | (0.066875) | (0.063574) | (0.021010) |
| α | 0.190444 | 0.139031 | 0.229460 | 0.105849 | 0.106370 | 0.186310 |
| | (0.002405) | (0.016063) | (0.000883) | (0.011381) | (0.010318) | (0.002591) |
| β | 0.734452 | 0.725200 | 0.747553 | 0.831860 | 0.831938 | 0.745718 |
| | 0.000000 | (0.000000) | (0.000000) | (0.000000) | (0.000000) | (0.000000) |

Cycle 1 because of the global economy's lockdown owing to the virus, and the fatality rate was rising daily, particularly in European nations. In this case, the Islamic markets are extra volatile as equated to their underlying indices. However, once the lockdown condition is suspended from the economy, the returns show the stability that is visible in the chart also. Furthermore, the GARCH results show significant shock perseverance and positive AR and MA at a 1% level of significance, as shown in Table 7.

The returns plot for the post-COVID-19 time is displayed in Figure 3. It is also shown that the markets are more

**Figure 3.** ***Volatility Clustering Post-COVID-19 Cycle 1***

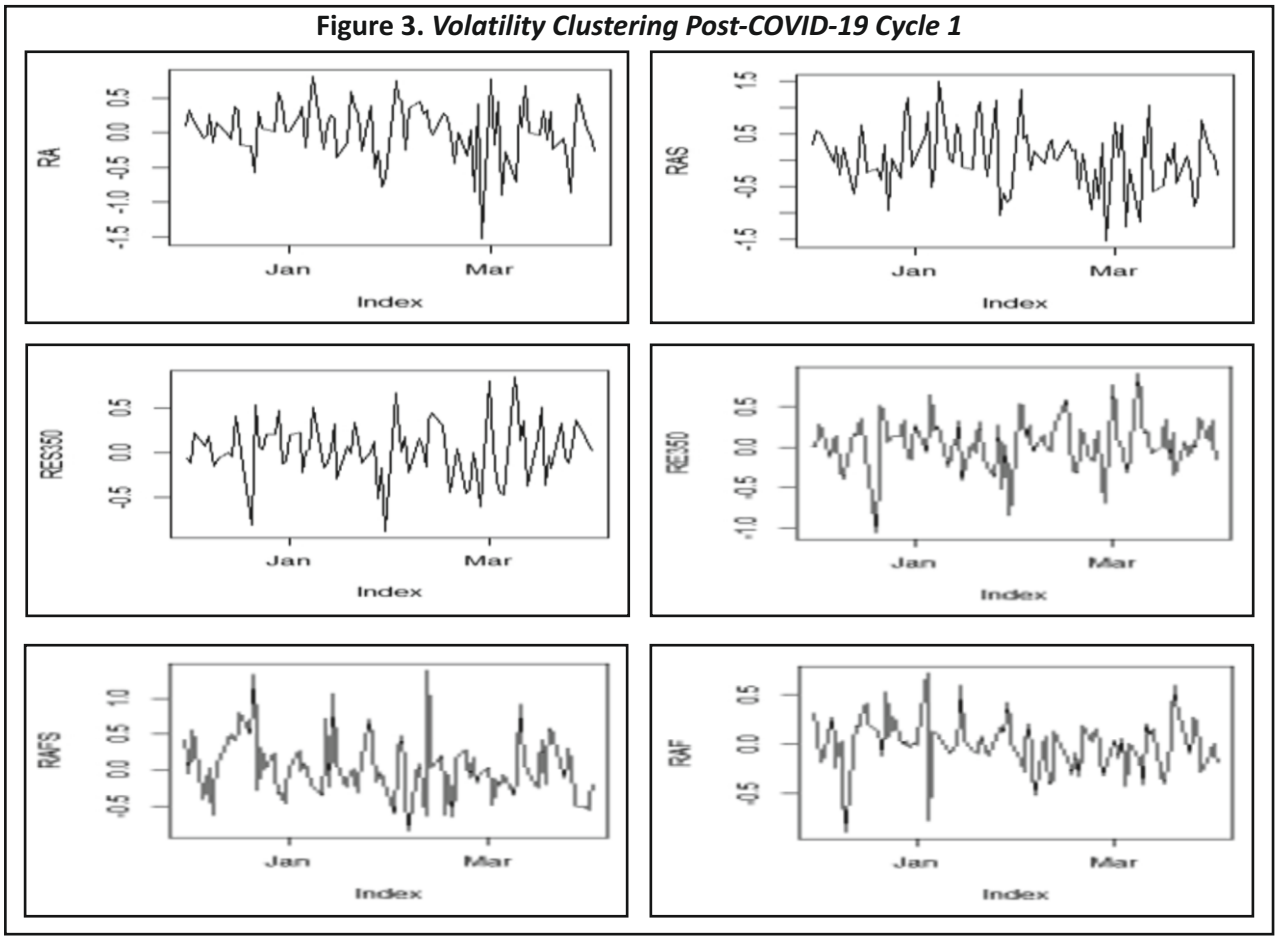

**Table 8.** ***GARCH (1,1) of Post-COVID-19 Cycle 1***

| | RA | RAS | RAF | RAFS | RE350 | RES350 |
|---|---|---|---|---|---|---|
| μ | 0.074032 | 0.035653 | 0.001879 | 0.036607 | 0.046403 | 0.031955 |
| | (0.084359) | (0.58103) | (0.94884) | (0.43438) | (0.18005) | (0.35232) |
| Ω | 0.035333 | 0.013621 | 0.00000 | 0.00000 | 0.000076 | 0.000350 |
| | (0.077671) | (0.24110) | (0.99997) | (0.99992) | (0.98065) | (0.89699) |
| α | 0.332232 | 0.000000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| | (0.088529) | (1.00000) | (1.00000) | (1.0000) | (1.00000) | (1.00000) |
| β | 0.507904 | 0.956306 | 0.997585 | 0.998894 | 0.998998 | 0.998998 |
| | (0.000663) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |

volatile. Table 8 reveals that α and β both are positive, which shows the presence of volatility in the market, and the positive value of the asymmetric term shows that pessimistic shocks have a stronger effect than optimistic shocks.

Figure 4 represents the returns of COVID-19. From May to July, the second wave of COVID-19 arose in the economy due to the lack of proper medical facilities; the death rate was extremely high, and again, lockdowns were also imposed, which affected the world market strongly and caused all markets to show the high volatility.

**Figure 4.** ***Volatility Clustering During COVID-19 Cycle 2***

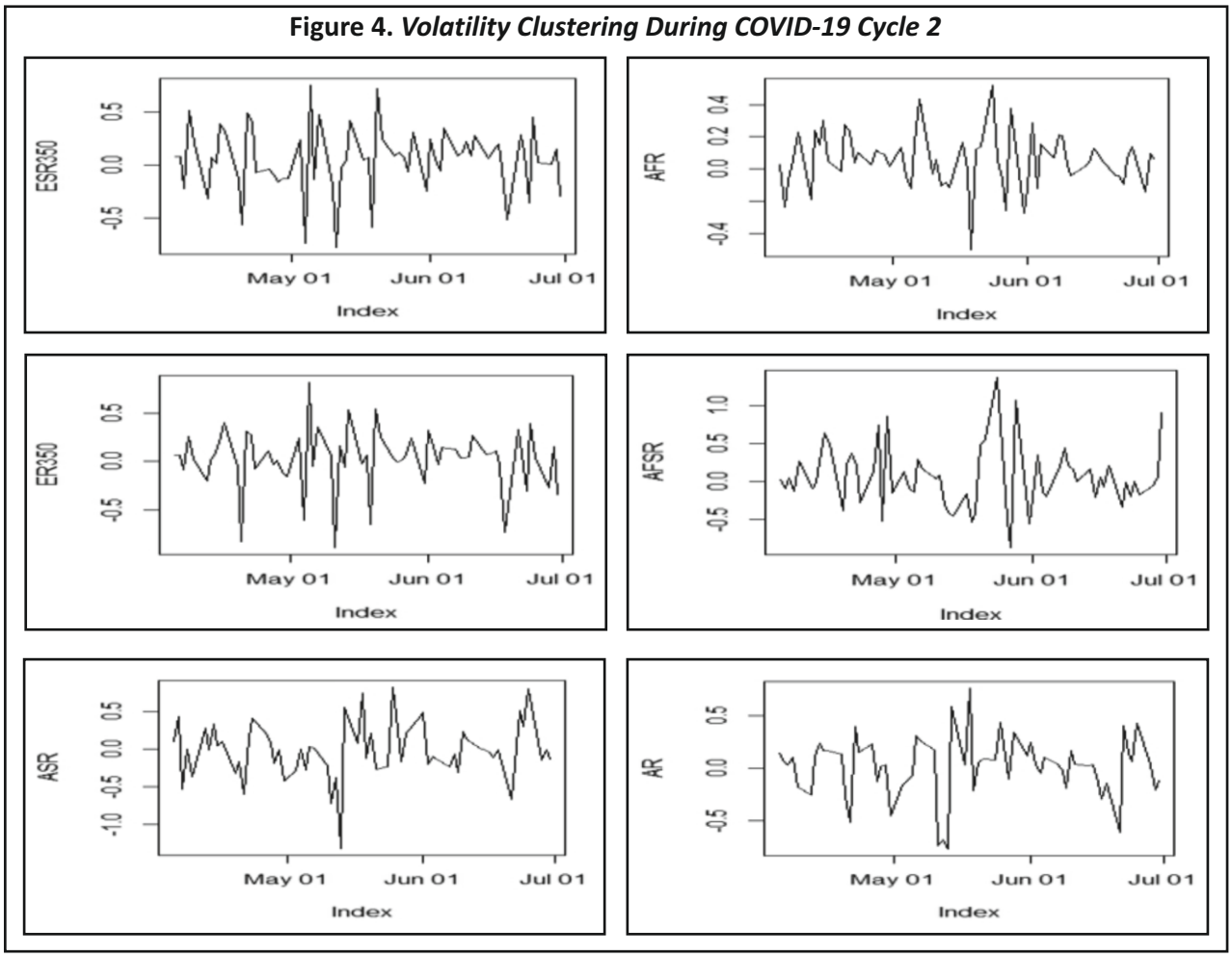

**Table 9.** ***GARCH (1,1) of During COVID-19 Cycle 2***

| | AR | ASR | AFR | AFSR | ER350 | ESR350 |
|---|---|---|---|---|---|---|
| μ | 0.009959 | –0.015661 | 0.050717 | 0.033863 | 0.030107 | 0.049129 |
| | (0.764580) | (0.735407) | (0.018135) | (0.485441) | (0.43496) | (0.20198) |
| Ω | 0.021220 | 0.008740 | 0.000000 | 0.069420 | 0.00000 | 0.00000 |
| | (0.192993) | (0.045957) | (1.00000) | (0.055681) | (0.99995) | (1.00000) |
| α | 0.257127 | 0.00000 | 0.000000 | 0.602283 | 0.00000 | 0.00000 |
| | (0.102849) | (1.00000) | (0.999999) | (0.066126) | (1.00000) | (1.00000) |
| β | 0.498864 | 0938792 | 0.998508 | 0.081468 | 0.998953 | 0.996603 |
| | (0.030748) | (0.000000) | (0.00000) | (0.803267) | (0.00000) | (0.00000) |

Table 9 shows the results of the coefficients of AR and MA, which are significant and optimistic, which means volatility is present in all markets. The results of GARCH analysis are also significant at a 1% level of significance, which means negative news impacts more as compared the positive news.

The post-COVID-19 cycle 2 returns, which cover the period of August 2021 to December 2022, are shown in Figure 5. The lockdown is removed from the economy, and the market comes to its stability rate. However, the

**Figure 5.** ***Volatility Clustering Post COVID-19 Cycle 2***

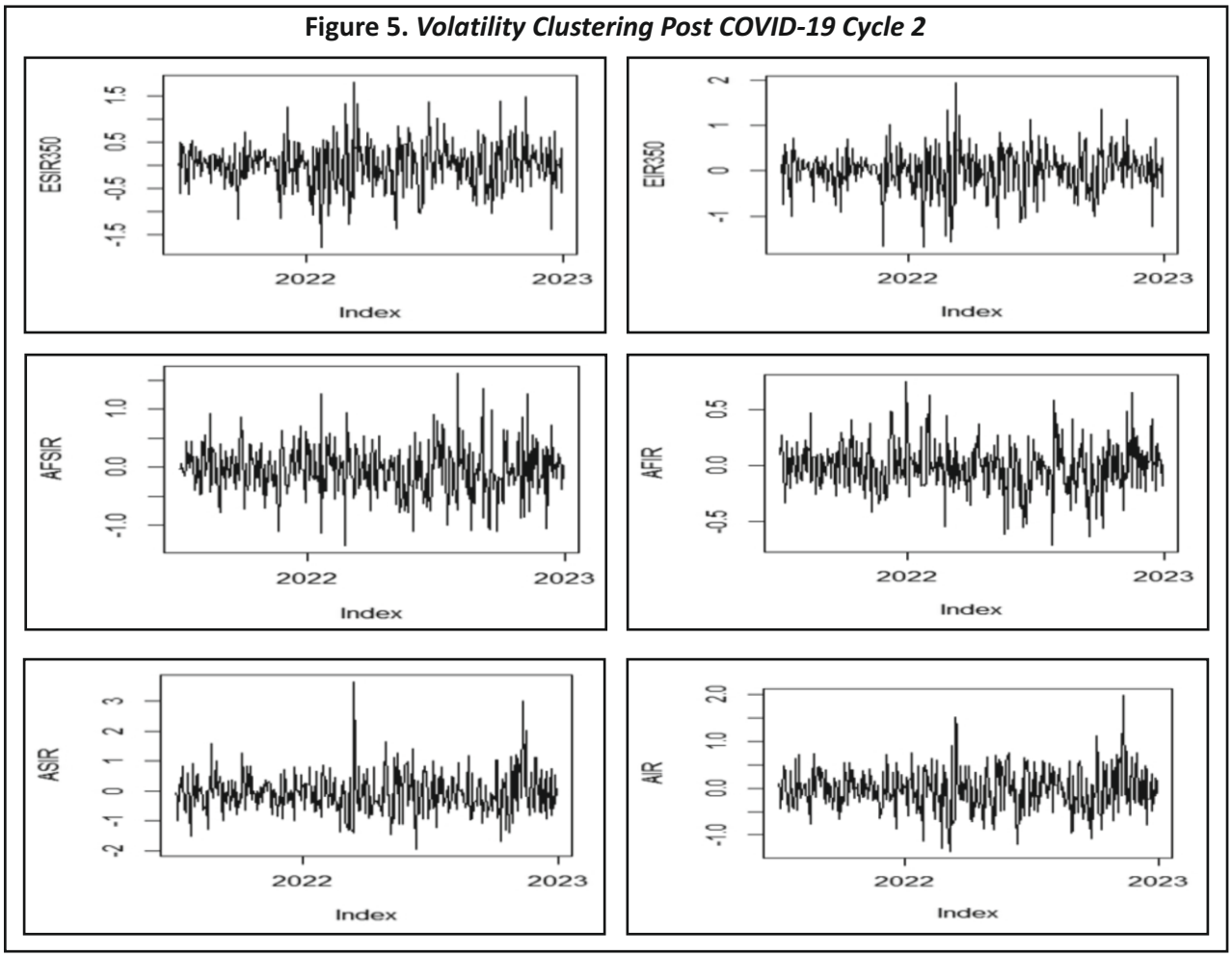

**Table 10.** ***GARCH (1,1) of Post-COVID-19 Cycle 2***

| | AIR | ASIR | AFIR | AFSIR | EIR350 | ESIR30 |
|---|---|---|---|---|---|---|
| μ | –0.027021 | –0.043963 | 0.013627 | –0.033893 | 0.016342 | 0.014166 |
| | (0.18232) | (0.13846) | (0.20126) | (0.10405) | (0.44097) | (0.51341) |
| Ω | 0.007212 | 0.019500 | 0.000062 | 0.004068 | 0.023485 | 0.012257 |
| | (0.21266) | (0.14078) | (0.58382) | (0.25479) | (0.00712) | (0.06371) |
| α | 0.077321 | 0.086369 | 0.000000 | 0.24175 | 0.164727 | 0.150726 |
| | (0.03431) | (0.00620) | (1.00000) | (0.10037) | (0.00238) | (0.00306) |
| β | 0.885906 | 0.868369 | 0.999000 | 0.953812 | 0.733578 | 0.807155 |
| | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) | (0.00000) |

market shows volatility due to various reasons. Table 10 shows the results of the GARCH (1,1) model with all markets, and it is observed that the coefficients of α and β are significant, which shows the presence of volatility clustering. Negative news impacts the stock market strongly, but not for a long period.

We use the GARCH model to find out the residuals for applying the Copula model to find out the dependency structure among the variables.

## Copula Model and Estimations

### *Sklar's Theorem*

The copula variety employed in our study comprises the elliptical copulas, i.e., Gaussian copula, Student-*t* copula, and some Archimedean copula, which includes the Clayton copula, the Frank copula, and the Gumbel copula. The

**Table 11.** ***Pre COVID-19***

| | Pairs | Copula | Par1 | Par2 | Kendall's Tau |
|---|---|---|---|---|---|
| **Tree 1** | ESI350–ASI | Frank | 1.2 | 0.0000 | 0.13 |
| | ESI350–AFI | BB7 | 2.5 | 1.96 | 0.62 |
| | ESI350–AFSI | Frank | 2.38 | 0.0000 | 0.25 |
| | ESI350–AI | Student-*t* | 0.31 | 3.86 | 0.2 |
| | ESI350–ES350 | Rotated Tawn Type 1 180* | 3.24 | 0.06 | 0.06 |
| **Tree 2** | AI–ASI\|ESI350 | Independence | 0.0000 | 0.0000 | 0.00000 |
| | AI–AFI\|ESI350 | Gumbel | 1.22 | 0.0000 | 0.18 |
| | AI–AFSI\|ESI350 | Gumbel | 2.65 | 0.0000 | 0.62 |
| | AI–ES350\|ESI350 | Independence | 0.0000 | 0.0000 | 0.00000 |
| **Tree 3** | ES350–ASI\|ESI350–AI | Rotated Tawn Type 1 180* | 2.05 | 0.45 | 0.29 |
| | ES350–AFI\|ESI350–AI | Rotated Joe 90* | –1.18 | 0.0000 | –0.09 |
| | ES350–AFSI\|ESI350–AI | Independence | 0.0000 | 0.0000 | 0.0000 |
| **Tree 4** | AFI–ASI\|ES350–ESI350–AI | Joe | 1.3 | 0.0000 | 0.14 |
| | AFI–AFSI\|ES350–ESI350–AI | Independence | 0.0000 | 0.0000 | 0.0000 |
| **Tree 5** | AFSI–ASI\|AFI–ES350–ESI350–AI | Independence | 0.0000 | 0.0000 | 0.0000 |

***Note.*** *Degree of Copula.

category of Archimedean copulas was given by Ling (1965) but recognized by Schweizer and Sklar (1961) in the research of *t*-norms. They are interesting because they are not elliptic copulas and permit us to represent a wide range of various dependency patterns. We concentrate on one-parameter of Archimedean copulas. The study

**Table 12.** ***During COVID Cycle***

| | Pairs | Copula | Par1 | Par2 | Kendall's Tau |
|---|---|---|---|---|---|
| **Tree 1** | AFSI–EI350 | Student-*t* Copula | 0.93 | 4.97 | 0.76 |
| | AFSI–AFI | Rotated Tawn Type 2, 180* | 1.25 | 0.06 | 0.03 |
| | AFSI–ASI | Rotated Tawn Type 1, 270* | –2.0 | 0 | 0 |
| | AFSI–AI | BB1 | 0.52 | 1.09 | 0.27 |
| | AFSI–ESI350 | Survival Clayton | 0.21 | 0.0000 | 0.1 |
| **Tree 2** | AI–ESI350\|AFSI | BB8 | 2.12 | 0.98 | 0.36 |
| | AI–EI350\|AFSI | Independence | 0.0000 | 0.0000 | 0.00000 |
| | AI–AFI\|AFSI | Rotated Tawn Type 2, 180* | 1.32 | 0.12 | 0.06 |
| | AI–ASI\|AFSI | Survival Clayton | 0.06 | 0.0000 | 0.36 |
| **Tree 3** | ASI–ESI350\|AFSI–AI | BB8 | –1.5 | –0.75 | –0.09 |
| | ASI–ES350\|AFSI–AI | Gaussian | –0.080 | 0.0000 | –0.05 |
| | ASI–AFI\|AFSI–AI | BB7 | 1.09 | 0.04 | 0.06 |
| **Tree 4** | AFI–ESI350\|AFSI–AI–ASI | Rotated Tawn Type 1, 90* | –4.13 | 0.01 | –0.01 |
| | AFI–ES350\|AFSI–AI–ASI | Independence | 0.0000 | 0.0000 | 0.0000 |
| **Tree 5** | ESI350\|AFSI–AI–ASI–AFI–EI350 | Rotated Joe | –1.04 | 0.0000 | –0.02 |

***Note.*** *Degree of Copula.

**Table 13.** ***Post-COVID Cycle 1***

| | Pairs | Copula | Par1 | Par2 | Kendall's Tau |
|---|---|---|---|---|---|
| **Tree 1** | AI–ASI | Survival Gumbel | 2.52 | 0.0000 | 0.6 |
| | AI–AFI | Survival Gumbel | 1.15 | 0.0000 | 0.13 |
| | AI–AFSI | Tawn Type 1 | 2.51 | 0.06 | 0.06 |
| | AI–ES350 | Gaussian | 0.57 | 0.0000 | 0.39 |
| | AI–ESI350 | BB1 | 0.64 | 1.15 | 0.09 |
| **Tree 2** | ESI350–ASI\|AI | Frank | 0.86 | 0.0000 | |
| | ESI350–AFSI\|AI | Independence | 0.0000 | 0.0000 | 0.00000 |
| | ESI350–AFI\|AI | Independence | 0.0000 | 0.0000 | 0.00000 |
| | ESI350–ES350\|AI | Student-*t* | 0.91 | 5.68 | 0.73 |
| **Tree 3** | AFI–ASI\|ESI350–AI | Rotated Clayton 270* | –0.2 | 0.0000 | –0.13 |
| | AFI–AFSI\|ESI350–AI | Frank | 0.74 | 0.0000 | 0.08 |
| | AFI–ES350\|ESI350–AI | Independence | 0.0000 | 0.0000 | 0.0000 |
| **Tree 4** | ES350–ASI\|AFI–ESI350–AI | Independence | 0.0000 | 0.0000 | 0.0000 |
| | ES350–AFSI\|AFI–ESI350–AI | Independence | 0.0000 | 0.0000 | 0.0000 |
| **Tree 5** | AFSI–ASI\|ES350–AFI–ESI350–AI | Independence | 0.0000 | 0.0000 | 0.0000 |

***Note.*** *Degree of Copula.

examines the different types of copulas and determines if they are appropriate for financial data. The copula methods considered in this research include the elliptical copulas, i.e., student *t*-copula, Gaussian copula, and Archimedean copulas families like Gumbel copula, Frank copula, Joe copula, and Clayton copula. Tables 11 to 15 represent the outcomes of the copula parameters.

**Table 14. *During COVID Cycle 2***

| | Pairs | Copula | Par1 | Par2 | Kendall's Tau |
|---|---|---|---|---|---|
| **Tree 1** | AFI–AI | Independence | 0.0000 | 0.0000 | 0.000 |
| | AFI–ASI | Independence | 0.0000 | 0.0000 | 0.000 |
| | AFI–AFSI | Rotated Tawn Type 2 180* | 1.78 | 0.32 | 0.2 |
| | AFI–ES350 | Clayton | 0.44 | 0.0000 | 0.18 |
| | AFI–ESI350 | BB7 | 3.34 | 3.82 | 0.72 |
| **Tree 2** | ES350–AI\|AFI | Rotated Joe 90* | –1.23 | 0.0000 | –0.12 |
| | ES350–ASI\|AFI | Gaussian | 0.64 | 0.0000 | 0.44 |
| | ES350–AFSI\|AFI | Rotated Tawn Type 1 270* | –20 | 0.03 | –0.03 |
| | ES350–ESI350\|AFI | Frank | –1.18 | 0.0000 | –0.19 |
| **Tree 3** | AFSI–AI\|ES350–AFI | Survival BB7 | 1.95 | 1.08 | 0.5 |
| | AFSI–ASI\|ES350–AFI | Rotated Tawn Type 2 180* | 2.5 | 0.16 | 0.14 |
| | AFSI–ESI350\|ES350–AFI | Independence | 0.0000 | 0.0000 | 0.000 |
| **Tree 4** | ASI–AI\|AFSI–ES350–AFI | Independence | 0.0000 | 0.0000 | 0.000 |
| | ASI–ESI350\|AFSI–ES350–AFI | Independence | 0.0000 | 0.0000 | 0.000 |
| **Tree 5** | ESI350–AI\|ASI–AFSI–ES350–AFI | Rotated Tawn Type 2 90* | –7.43 | 0.08 | –0.07 |

***Note.*** *Degree of Copula.

**Table 15. *Post-COVID Cycle 2***

| | Pairs | Copula | Par1 | Par2 | Kendall's Tau |
|---|---|---|---|---|---|
| **Tree 1** | AFI–AI | Gaussian | 0.39 | 0.0000 | 0.26 |
| | AFI–ES350 | Rotated Tawn Type 1 180* | 1.21 | 0.25 | 0.08 |
| | AFI–ASI | Gumbel | 1.04 | 0.0000 | 0.03 |
| | AFI–AFSI | Gaussian | 0.46 | 0.0000 | 0.31 |
| | AFI–ESI350 | Student-*t* | 0.94 | 9.22 | 0.78 |
| **Tree 2** | AFSI–AI\|AFI | Gaussian | 0.8 | 0.0000 | 0.59 |
| | AFSI–ES350\|AFI | Independence | 0.0000 | 0.0000 | 0.0000 |
| | AFSI–ASI\|AFI | Rotated Joe 90* | –1.06 | 0.0000 | –0.03 |
| | AFSI–ESI350\|AFI | Clayton | 0.23 | 0.0000 | 0.1 |
| **Tree 3** | ASI–AI\|AFSI–AFI | Independence | 0.0000 | 0.0000 | 0.0000 |
| | ASI–ES350\|AFSI–AFI | Gaussian | 0.65 | 0.0000 | 0.45 |
| | ASI–ESI350\|AFSI–AFI | Rotated Clayton 270* | –0.14 | 0.0000 | 0.06 |
| **Tree 4** | ESI350–AI\|ASI–AFSI–AFI | Tawn Type 1 | 2.32 | 0.01 | 0.01 |
| | ESI350–ES350\|ASI–AFSI–AFI | Tawn Type 1 | 4.07 | 0.01 | 0.01 |
| **Tree 5** | ES350–AI\|ESI350–ASI–AFSI–AFI | Rotated Joe 270* | –1.04 | 0.0000 | –0.02 |

***Note.*** *Degree of Copula.

The Gaussian copula is selected once in the normal period and six times during the crisis phase. Over the normal and crisis eras, the Archimedean copula is the optimal dependency model for overall periods. Except for the Frank copula, which is never relevant, the remaining copulas are selected just once, depending on the market period. The reduced governance of the *t*-student copulas on other copulas throughout the subperiods compared to the overall findings is due to changes in the stochastic characteristics of the index returns as well as the possibility of detecting extremely infrequent observations.

Lastly, the dependency structure is symmetrical for almost all market pairs in the post-COVID-19 cycle 2 time period, irrespective of the pre-COVID-19 time period. In all other time periods, it exhibits asymmetric patterns (upper tail dependence) across the normal period. The tail dependency has been stronger in post-COVID cycle 2 among the ASIR|AIR-AFIR-AFSIR-EIR350-ESIR350, AFSIR|AIR-ASIR-EIR350, and ESIR350|AIR-ASIR-AFSIR-EIR350-ESIR350 compared to the other periods. Our results indicate a greater possibility of combined severe co-movements during COVID-19 cycle 2 of the crisis.

## Conclusion

The study examines the volatility pattern and dependency structure of both Islamic and conventional indices for all indices from January 1, 2017 to December 31, 2022, by using the GARCH model and Copula method. The outcomes suggest that conventional indices are more volatile in comparison to Islamic ones. The results suggest that throughout the epidemic era, the stock market, particularly the conventional market, became turbulent. In the case of another stock market, the COVID-19 period has no substantial influence on the volatility of stock prices of the underlying index as compared to the conventional index. The mean return before COVID-19 and during COVID-19 is calculated independently. The results demonstrate that with pessimistic mean returns, the share market suffered losses during the epidemic and post-COVID-19 cycle 2, while returns were positive prior to COVID-19, with the exception of the African frontier market, post-cycle 1, and during the COVID cycle 2 (except Asia Islamic market when the SDs are compared, it is clear that the deviation is greater during COVID-19 and post-COVID-19 cycle 1 era than pre-COVID-19 and during and post-COVID-19 cycle 2). Consequently, the price of stock indexes has changed significantly. Prior to COVID-19, the price was high, but it decreased throughout the COVID-19 pandemic until the first lockdown period, which ended at the end of March, after which it progressively increased.

In short, the findings indicate that the COVID-19 outbreak has impacted stock prices, increased volatility in Indian stock markets, and harmed the financial system. The GARCH results show the positive coefficients of AR and MA in all markets. The coefficients of $\alpha$ and $\beta$ are also significant, which implies that the market is persistent regarding the stock market shocks. In the post-COVID-19 time period, it reveals that $\alpha$ and $\beta$ both are positive, which shows the presence of volatility in the market, and the positive value of the asymmetric term shows that pessimistic shocks have a stronger effect than optimistic shocks. The results of the GARCH analysis are also significant at a 1% level of significance, which means negative news impacts more as compared to positive news. Finally, the lockdown is removed from the economy, and the market comes to its stability rate. However, the market shows volatility due to various reasons; it is observed that coefficients of $\alpha$ and $\beta$ are significant, which shows the presence of volatility clustering.

Regardless of the pre-COVID-19 time period, the dependence structure is symmetrical for approximately all the market pairs in the post-COVID-19 cycle 2 period of time. Over the usual period, it shows asymmetric patterns (upper-tail dependency) for all other time durations. As compared to the different periods, the tail dependency has been bigger in post-COVID-19 cycle 2 among the ASIR|AIR-AFIR-AFSIR-EIR350-ESIR350, AFSIR|AIR-ASIR-EIR350, and ESIR350|AIR-ASIR-AFSIR-EIR350-ESIR350. Our data indicates that joint severe co-movements are more likely to occur after post-COVID-19 cycle 2 of the crises.

## Implications

The implications and limitations show that the crisis has no impact on the Islamic market. The study is helpful for investors in making investment decisions related to their portfolio diversification and creating awareness among them. Insights from capital market studies can inform regulators about the need for new rules or adjustments to existing ones, especially in areas like insider trading, market manipulation, or financial stability. As markets globalize, the need for harmonized regulations across countries becomes more evident, influencing international cooperation and policy-making. As a result, this research attempts to present another very simple but innovative statistical analysis of the COVID-19 pandemic, taking the case of the global stock market.

## Limitations of the Study and Scope for Future Research

The study was limited to a few stock indices and will be enlarged by adding global markets with a more significant time duration. We used GARCH and Copula models; further studies will be done using Wavelet and DCC-GARCH models on different time durations, regions, and indices of Islamic and conventional indexes to analyze the volatility of the Islamic market.

## Authors' Contribution

Ms. Sumbul conceived the idea and developed qualitative and quantitative designs for the empirical study. Ms. Sumbul extracted research papers with high reputations, filtered these based on keywords, and generated concepts and codes relevant to the study design. Ms. Ziya Batul Rizvi verified the analytical methods and supervised the study. Ziya Batul Rizvi and Sumbul did the numerical computations on E-views and R and wrote the manuscript. Dr. Saif Siddiqui guided us at every step of the current study. He motivated us and gave directions for conducting this research.

## Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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