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Stock Market Resilience: Evaluating Islamic and Conventional Indices through COVID-19 Waves

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ABSTRACT

The study examined the impact of the five COVID-19 waves on Pakistan's conventional (KSE-100) and Islamic (KMI-30) stock indices from March 3, 2020, to August 30, 2022. The DCC GARCH (1, 1) model found weak, predominantly negative connections between COVID-19 cases each day and stock returns. Visual data indicated a slight decrease in both indices as cases increased, reflecting previous findings on pandemics' adverse effects on stock markets. A thorough examination of the linkages between COVID-19 cases and financial indicators using Wavelet Coherence analysis highlighted intricate connections that are important to policymakers and financiers. Pakistan's KSE100 and KMI-30 indices showed a constant significant positive dynamic conditional association that persisted throughout the investigation. This challenges the perception that the Islamic index serves as a safe haven during financial crises. According to the research, Islamic stock markets, as reflected by the KMI-30, were not as protective or as good at hedging during crises like the COVID-19 pandemic. In fact, they were more susceptible to economic downturns. When navigating the effects of global health crises on financial markets, investors and policymakers must have a thorough understanding of these dynamics.

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1. Introduction

Researchers have extensively studied how stock markets respond to health emergencies, consistently finding adverse outcomes. Poor performance in capital markets during the Foot-and-Mouth Disease (FMD) epidemic was emphasized, for instance, by Pendell, Leatherman, Schroeder, and Alward (2007). The 2003 SARS pandemic also brought about significant economic disruption Chen, Jang, and Kim (2007) reported a 29% drop in share values in Taiwan's service sector within a month of the outbreak.

According to Hatmanu and Cautisanu (2021), the virus significantly lowered the values of the Bucharest Exchange Trading (BET) index. Furthermore, it was discovered by Zeng and Zhou (2021) that nations with greater GDP per person, health spending, and substantial foreign direct investment (FDI) from China suffered more severe financial consequences during health crises.

The impact of the outbreak on the stock index is investigated in this study using both conventional and Islamic criteria. Global disruptions never seen before have been caused by the COVID-19 pandemic in Wuhan, China. Since February 2020, when the first verified case was announced there, Pakistan has been hit by waves of infections. These infections have significantly influenced the nation's healthcare system, economy, and day-to-day living. Many industries have been badly hit, including retail, finance, and IT (Chaudhary, Bakhshi, & Gupta, 2020). The epidemic has caused notable price changes and volatility in the stock markets (He, Sun, Zhang, & Li, 2021; Narayan, Gong, & Ahmed, 2022; Sharma, 2020). However, there is a notable lack of research on the distinctions between Shariah-compliant and conventional investment principles during such crises. On the other hand, some studies have been done on how conventional and Shariah-compliant investment principles differ in times of crisis. COVID-19 presented unheard-of difficulties for the Islamic banking industry, often considered more resilient (Ghouse, Bhatti, Aslam, & Ahmad, 2023). Pakistan's leading market indices, KSE-100 and KMI-30, represent conventional and Islamic stocks, respectively. The KSE-100 index, established in 1991, includes 100 businesses selected based on free-float capitalization and industry representation. Launched in 2009, the KMI-30 index comprises 30 firms chosen through rigorous Shariah screening protocols. During the first lockdown in March 2020, the Pakistan stock market averaged a daily decrease of 1,500 points, exacerbated by rising interest rates, falling oil prices, and the unexpected emergence of the pandemic. Divergent opinions regarding the relative performance of Shariah-compliant firms and traditional stocks are found in the literature. According to specific research, such as Hasan, Mahi, Hassan, and Bhuiyan (2021), there was a close association between the two markets' degrees of volatility during the epidemic. While some studies showed that the Islamic index outperformed its counterparts, others, such as TÜKENMEZ, ŞAKA, and KIZGIN (2019), found no discernible return difference between conventional and Islamic indexes (Daruwala, 2022).

Recent studies have further illuminated these dynamics. Mzoughi, Amar, Belaid, and Guesmi (2022) investigated how the COVID-19 pandemic influenced Islamic and conventional stock markets globally, highlighting differences in resilience and recovery patterns; their findings also contribute to helping investors better adjust their investment strategies by revealing significant changes in market interdependence during the COVID-19 pandemic. A comparative analysis by Ghenimi, Chaibi, and Omri (2024) further illustrates these distinctions, showing that Islamic banks in the MENA region were more resilient and less risky than their conventional counterparts during the pandemic. This study revealed that Islamic banks performed better and were less impacted by the pandemic shock.

The main goals are to find out how COVID-19 affected both indices, look into the relationship between the indices and newly reported COVID-19 cases each day, investigate how the indices related to one another during different pandemic waves, and find out if these indices are hedges, diversifiers, or safe havens for one another. This study advances our understanding of the response of conventional and Islamic stock indices to medical emergencies, thereby supplying investors and decision-makers with valuable data. By analyzing the dynamic relationships between these indexes during the pandemic, this study aims to fully understand the financial market's response to unforeseen health crises, particularly in the context of conventional and Islamic principles in Pakistan.

This study will fill the gap in the Pakistan Stock Exchange (PSX) by Conventional (KSE100) & Islamic (KMI30) stock indices. Various studies have investigated the impact of COVID-19 on the performance of the Islamic index (KMI30), and some have explored the co-movement between COVID-19 metrics (Total number of cases, Total deaths) and both Islamic and conventional indices of the Pakistan Stock Exchange (PSX). However, these studies typically focus on the period corresponding to the first two waves of the pandemic. This study explores the linkages and dynamic conditional correlation between the Traditional and Islamic indices of the Pakistan stock exchange during different pandemic waves. In addition, it explores dynamic associations between COVID-19 (new daily cases) and Pakistan stock market indices during all waves.

1.1. Objectives of the Study

- Examine how COVID-19 has affected the conventional and Islamic index performance of the Pakistan Stock Exchange (PSX).
- Examine how the performance of the Pakistan Stock Exchange's Conventional (KSE-100) and Islamic (KMI-30) indices correlated with the number of new daily COVID-19 cases during the pandemic.
- Examine the dynamic correlation that existed during the epidemic between KSE-100 and KMI-30 indices.
- They are analyzing the relationship between the PSX's conventional and Islamic indices during different epidemic waves, paying particular attention to the first five COVID-19 waves.
- Investigate if conventional and Islamic indices support one another by serving as hedges, diversifiers, and safe haven assets.

1.2. Hypotheses of the Study:

- COV-19 significantly influences the performance of the Pakistan Stock Exchange's conventional and Islamic indices negatively.
- A dynamic link has been seen between the number of new daily COVID-19 cases and the performance of the Conventional (KSE-100) and Islamic (KMI-30) indices during a pandemic.
- The relationship between the conventional and Islamic indices, which varies throughout several pandemic waves, indicates variations in the first five waves of COVID-19.
- The conventional and Islamic indices can act as safe haven assets, hedges, or diversifiers for each other during the pandemic.
- The conventional and Islamic indices show a significant dynamic correlation during the pandemic.

We examined World Health Organization (WHO) statistics from March 3, 2020, to August 30, 2022, as well as daily closing prices of the KSE-100 and KMI-30 from Investing.com. These are the indicators that we selected to evaluate the performance of Conventional and Islamic stocks during the pandemic. We separated the data into five waves, each of which corresponded to a different stage of the COVID-19 epidemic, in order to comprehend the impact. Next, we looked at the changes in market behavior throughout these times. Additionally, in order to examine volatility patterns and the connection between the indices and recently disclosed COVID-19 cases, we computed daily rates of return from the closing prices. Using this method, we were able to investigate how these indices behaved as safe haven assets, diversifiers, or hedges at different points throughout the pandemic.

Understanding the COVID-19 pandemic's implications on different stock indices is crucial since it has presented special hurdles for the world's financial markets. By investigating how the dynamic link between the conventional (KSE-100) and Islamic (KMI-30) indices of the Pakistan Stock Exchange has changed during the course of the COVID-19 pandemic, this study aims to expand our understanding of finance and economics. Through examining the subtle differences between indices that comply with Sharia law and those that do not, this study offers important new understandings into how various investment vehicles behave in times of crisis.

2. Literature review

The spread of the COVID-19 pandemic impacted stock markets in many countries, and immediately after this outbreak, the markets experienced negative abnormal returns. This section briefly reviews existing studies regarding stock market volatilities and financial connectedness.

2.1. Market Response to the Pandemic

Recent research shows that the COVID-19 pandemic has influenced stock market performance globally. Abu-Alkhei, Alsharari, Khan, Ramzani, and Horam (2024) evaluated the results of the conventional and Islamic indices from 2017 to 2023, including the pandemic. Based on their findings, it appears that while conventional stock index tends to outperform Islamic index, they also exhibit higher volatility and risk. Additionally, no long-term co-integration links were found between 30 out of 31 pairs of conventional and Islamic indexes. Hossain (2024) Concluded that while Islamic and conventional indices in the Dhaka stock exchange move positively together, the Corona-Virus pandemic and geopolitical events like the Ukraine-Russia war have disrupted their positive momentum, revealing transient correlations and Granger causality from Islamic to conventional indices. Hamma, Ghorbel, and Jarboui (2024) study's findings indicate varying optimal ratio using DCC, ADCC, and Go-GARCH models during the COVID-19 pandemic, with DJCOM showing exceptional effectiveness. These insights are crucial for informing portfolio strategies amidst market volatility, enhancing risk management practices in Islamic and Conventional financial contexts.

Ghouse et al. (2023) examined the effect of the five day-to-day waves and recently confirmed COVID-19 cases on the version of the (KMI)-30. Based on the findings, it appears that COVID-19 has a negative asymmetric impact during each wave, but the effect decreases with each additional wave. COVID-19 has significantly negatively influenced KMI-30 performance throughout the given period. Afzal, Choudhury, and Kamran (2023) examined a copula-based DCC-GARCH model and the EVT theory for unpredictability capturing, examining the estimated time-varying dynamics and dependencies between the portfolios of the Pakistani and Shanghai stock markets. According to their model's findings, PSX and SSE's significant portfolios depend more on one another. The outcomes of the dependence structure then estimate the spillover effect of SSE over PSX positively. Rehman et al. (2021) investigated the impact of Coronavirus disease on the stock returns and volatility of four regions, including GCC, SAARC, BRIC, and G7, of conventional and Islamic indices. The findings discovered that the Coronavirus disease had a more significant impact on the return and volatility of traditional and Islamic stock markets, except Qatar, where the Qatar Islamic index (TRQAPI) was the least affected during the coronavirus disease.

Sundarasen, Kamaludin, and Ibrahim (2023) investigated the wavelet spectrum analysis to examine market volatilities in ASEAN and GCC countries before and during the COVID-19 pandemic. It reveals that ASEAN countries exhibited higher volatility during the pandemic, with some Shari'ah indexes being more volatile than conventional index. The study contributes insights into the dynamic relationship between health and financial crises, particularly in the context of Islamic equities, and offers valuable guidance for investors. Tabash, Sahabuddin, Abdulkarim, Hamouri, and Tran (2023) examined the relationship between stock market returns in developing countries (Malaysia, Indonesia, and China) and developed countries (the United States, the United Kingdom, and Japan), comparing Shari'ah-compliant and conventional indices from October 2007 to December 2021. They used multivariate GARCH-DCC, wavelet power spectrum, and coherence transform techniques to assess market co-movements and volatility. According to their findings, Shariah indices in developing markets had lower volatility and potential diversification benefits, whereas developed market correlations were more favorable, with Japanese Shariah indices providing opportunities for US investors. The study has implications for investors and policymakers, emphasizing the importance of diversification strategies and additional research into various asset classes and advanced econometric methods. Munir et al. focused on Pakistan's Karachi Stock Exchange and provided a distinctive viewpoint on the effect of a pandemic on Equity markets. It disproves the widely held belief that pandemics cause stock market declines and highlights a unique trend in a developing nation. According to this study, there is a negative correlation between the KSE-100 index performance and deaths across all quantiles in Pakistan but a positive correlation with confirmed and recovered cases. The robust findings contributed significantly to the body of information about the economic repercussions of the Coronavirus in developing countries and demonstrated the need for updated health –finance legislation and enhanced financial literacy programs.

The COVID-19 epidemic has caused a health crisis that has had a lasting influence on global financial markets, affecting both conventional and Islamic stocks. Aljaed conducted a study on how the pandemic affected various markets and their interconnections, using Wavelet correlation to uncover interesting insights. Interestingly, while conventional markets did not show a significant association, the number of COVID-19 deaths emerged as crucial factors within Islamic stock markets. Moreover, a positive correlation was identified between the MSCI Emerging Asia Index, the Morgan Stanley Capital international (MSCI) Emerging Asia Islamic index, and the number of COVId-19 deaths. In contrast there were mixed effects and uncertainties observed in the relationship between crude oil prices and exchange rates within the MSCI Gulf Corporation council (GCC) countries, affecting both conventional and Islamic indices differently. The COV-19 outbreaks had a significant and detrimental impact on the conventional and Islamic stock indices of the Pakistan Stock Exchange, as demonstrated by Bhutto, Khan, Khan, and Matlani (2022). The analysis reveals long-lasting adverse effects of Corona-Virus on stocks, with particular weaknesses seen in industries like commercial banks, oil and gas exploration, and marketing. At the same time, pharmaceuticals and automobiles exhibited relatively little impact. Ali, Khattak, Khan, and Khan (2023) investigated the effect of COV-19 on conventional indices and Islamic indices within the ASEAN region. The results display that COV-19 has unexpectedly decreased unpredictability in Islamic stocks. Islamic equity is implied to be a robust asset class for pandemic situations, encouraging long-term economic growth through wise investment. Wavelet coherency and the DCC-GARCH (1, 1) model remained toward examine the effect of COVID-19 on stock price correlation in the six GCC countries (Aliani, Al-kayed, & Boujlil, 2022).

Özdemir (2022) examined the wavelet-based, DCC-GARCH, and EGARCH models and the return and volatility spillover among eight significant cryptocurrencies. The results showed positive shocks, increased volatility, and COVID-19 amplified spillover, mainly in Bitcoin, Ethereum, and Litecoin markets. These results point to increased risk-taking and herding behaviour among investors during the pandemic, which may have caused unexpected price drops and Highlighted fears about the openness and security of cryptocurrency markets. Hidayah and Swastika (2022) investigated the MGARCH-DCC and examined the correlations and volatility of Indonesian Islamic, SRI, and conventional stocks during the COVID-19 pandemic. Unexpectedly, it shows that the Islamic index is the most efficient and volatile, offering no co-movement with the SRI and conventional index. That illustrates the effectiveness and resilience of Indonesian Islamic stocks throughout the pandemic. Silva (2022) examined the effect of the COV-19 pandemic on financial markets in both emerging and developed markets. According to the findings based on the asymmetric EGARCH model, the epidemic had a negative and statistically significant consequence on average stock market returns. Furthermore, COVID-19 significantly increased stock return volatility, implying a greater sensitivity to adverse shocks and thus distorting stock market performance during this crisis.

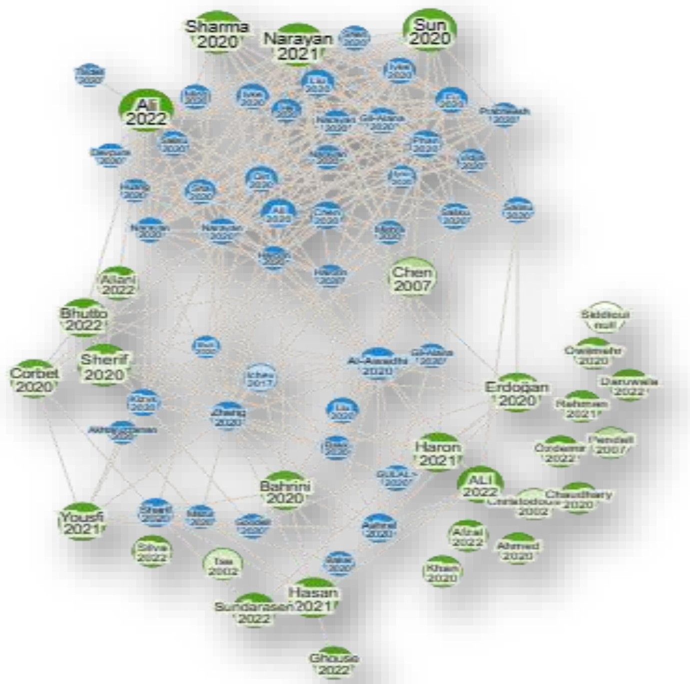

Figure 1: Literature Visualization

Yousfi, Zaied, Cheikh, Lahouel, and Bouzgarrou (2021) analysis of COVID-19's effects looked at risk sharing concerning the US (S&P 500) and China's CSI-300 before and after the crisis. It investigated links between global COVID-19 metrics, S&P 500 performance, and US uncertainty gauges while assessing how imbalanced shocks influenced their correlation. Employing DCC-GARCH, ADCC GARCH models, and wavelet coherence, the study unveiled amplified volatility spillover during the pandemic and contagion during the rapid US COVID-19 spread. Samadi, Owjimehr, and Halafi (2021) examined the Wavelet Coherence Analysis; the study evaluated co-movements across significant financial markets in Iran during high uncertainty (2014-2020). It discovered that oil had a low correlation with the stock exchange, exchange rate, and gold markets, implying that it can be a good option for risk-averse investors and a potential source of government revenue under sanctions.

Furthermore, amid unstable conditions such as sanctions or pandemics, gold's co-movement with the exchange rate highlights its importance in determining portfolio risk, offering policymakers knowledge on stabilizing the gold market through foreign exchange management. Hasan et al. (2021) investigated the global influence of COVID-19 on financial markets, performed through conventional and Islamic stock market indices. Their findings imply that both equity markets had exhibited increased volatility since the beginning of March when COVID-19 emerged as a worldwide pandemic. Additional findings suggested a strong connection between conventional and Islamic stock markets, with frequent synchronized movements observed throughout the study period. Sattar and Siddiqui (2021) used continuous wavelet transforms and MGARCH-DCC to examine the dynamic relationship between the KSE 100 and KMI 30 indices in the Pakistani stock market. The results show that while return volatility varies with market conditions, it tends to stabilize over time. Due mainly to Pakistan's large number of cases, the COVID-19 shock significantly increased return uncertainty, and in the medium to long term, market returns showed a stronger correlation. Rehman et al. (2021) investigated the dynamic characteristics of volatility in stock returns on the Pakistan Stock Exchange, concentrating on the KSE-100 and KMI-30 indices. The study covers the period from June 2009 to August 2020. The research established that both indices display volatility clustering through various time-series analysis methods, such as ADF (Augmented Dickey-

Fuller) and ARCH (Autoregressive Conditional Heteroscedasticity) modelling. This clustering indicates the presence of both high and low volatility periods over the studied timeframe. The study suggested that these stock returns respond more to negative news, implying that investors experience increased volatility during unfavorable market conditions. Elshqirat (2021) contrasted the performance of conventional indexes with Islamic stock indices in GCC countries during the coronavirus. The findings revealed no significant performance difference between conventional indices and Islamic indices throughout the pandemic, implying that Islamic indices provide limited diversification benefits in this specific context.

Ahmed (2020) evaluated VIX correlations; they found adverse relationships with both market types after using the contagion theory to analyze the pandemic impact on Turkey's conventional and Islamic stock markets. The results demonstrated lower correlations between PI and VIX than ISE and VIX. ISE-VIX correlations increased after COVID-19, but PI-VIX correlations decreased, showing that Islamic markets were more resilient to global shock than the conventional Turkish stock market. Corbet, Larkin, and Lucey (2020) examined the volatility and dynamic correlations in Chinese stock markets, revealed light on the complex relationships between financial assets during crises; the studies conducted indicate that, during the COVID-19 epidemic, cryptocurrencies such as Bitcoin did not act as safe havens, but instead significantly exacerbated market volatility. Bahrini and Filfilan (2020) investigated the effects of the outbreak on stock markets by analyzing the impact of Corona-virus inveterate cases and deaths on the regular returns of major equity indices in the Gulf Cooperation Council (GCC) nations. The study finds that the GCC stock markets react negatively to COVID-19-confirmed deaths using a panel data regression analysis. However, the number of confirmed cases does not seem to have as much of an impact. The study highlighted that the increase in confirmed deaths during the COVID-19 outbreak coincided with a decrease in the average daily return of the major stock market indices in the GCC countries.

In this study utilized event study methodology, Khan, Elahi, Ullah, and Khattak (2020) examined the effect of the COV-19 epidemic on the stock market returns of 3 prominent Pakistani indices: KSE-(100), KSE-(30), and KMI-(30). Following the technique of a previous study He et al. (2021), they used a 61-day event window with a 160–day estimation timeframe. The results showed that the pandemic negatively affected all three indices during the post-event interval. The findings revealed the pandemic's significant and negative effect on all three indices, persisting during the post-event window. Notably, the t-values indicated a substantial adverse reaction from day 12 to day 28 following the onset of the pandemic.

3. Methodology

3.1. Data and Variables

In our analytical study, we selected the daily closing price of the KSE-Meezan Index (KMI-30) to represent the Islamic index and the Karachi Stock Exchange 100 index (KSE-100) to represent a conventional index within the Pakistan Stock Exchange (PSX). We track new daily cases in Pakistan regarding information linked to COVID-19; figure (a) below shows the daily prices of both indices during the whole period. 616 observations from the World Health Organization (WHO) and Investing are included in our dataset, which spans the period from March 3, 2020, to August 30, 2022. Using COVID-19 waves as a baseline, the data was divided into five sections. According to pandemic waves data, the first wave started from 03/March/2020 to 31/August/2020. The total number of observations is 122. The second wave started from 01/September/2020 to 24/February/2021; Total observations are 124. The third wave started from 25/February/2021 to 30/July/2021; the Total observation are 102. The fourth wave began from 01/August/2021 to 31/December/2021; Total observations are 107. The fifth wave is from 01/January /2022 to 30/August/2022; Total observations are 161. The indices transformed into daily rate of return, as represented in equation (1)

$$RT = ln\,(p_t/p_{t-1}) \tag{1}$$

In this equation, R_T represents the daily log returns, determined based on each equity index's daily-adjusted closing prices at t and t-1, denoted as p_t and p_{t-1}, respectively.

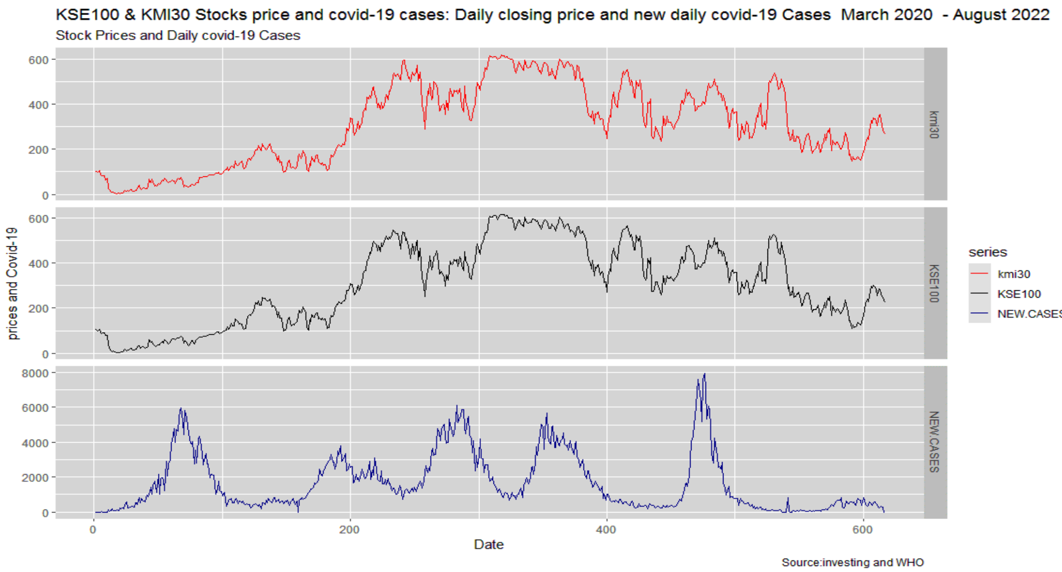

Figure 2: New Daily Cases of COVID-19

3.2. Empirical Model

3.2.1. The DCC-GARCH Model

The Dynamic Conditional Correlation GARCH (DCC-GARCH) model is a powerful method for analyzing the relationship between financial data and dynamic correlations. This model is beneficial for capturing changes in conditional correlations over time. It was developed by various researchers, including (Christodoulakis & Satchell, 2002; Engle, 2002; Tse & Tsui, 2002). The Constant Conditional Correlation GARCH (CCC-GARCH) model, initially proposed by Christodoulakis and Satchell (2002), assumes a time-independent conditional correlation matrix. On the other hand, the DCC-GARCH models, introduced by Engle (2002) and later extended by Tse and Tsui (2002), enable the consideration of time-dependent conditional correlation matrices. These models work well with high-dimensional and multivariate datasets.

The fundamental concept of the DCC-GARCH model is to periodically split the coronavirus matrix into the correlation matrix (Rt) and the conditional standard deviations (Dt). This split allows for the representation of evolving correlations between financial assets because conditional correlation is not stable and can vary over time.

Our study investigated the dynamic relationship between the KSE-100 and KMI-30 indices of the Pakistan Stock Exchange (PSX) throughout different pandemic waves using the DCC-GARCH model. The model takes this variability into account and helps explain how the correlation structure between various indices changes, even if these conditional correlations can alter as market conditions change.

3.2.2. Time-Varying Correlation Matrix (Rt)

The core of the DCC-GARCH model is the time-varying correlation matrix, denoted by the symbol Rt, which stands for the conditional correlations between the two indices. Within the model:

$$R|£t - 1 \sim \mathrm{N}\,(0, \mathrm{Ht}) \tag{2}$$

And

$$H_t = D_t R_t D_t \tag{3}$$

In this case, Ht is defined as the product of the diagonal matrix Dt, which is made up of the time-varying standard deviation from univariate GARCH models, and the time-varying correlation matrix Rt. This time-varying correlation structure allows for a more realistic depiction of the evolving ties between the Islamic KMI-30 and conventional KSE-100 indices during numerous epidemic waves.

3.2.3. Model Estimation and Likelihood

The log-likelihood function of this estimator is given by:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log((||\,\mathbf{Dt}|)) + \boldsymbol{log}(|\mathbf{Rt}|) + \boldsymbol{\varepsilon R_t^{-1}}) \tag{4}$$

The equation defines a univariate GARCH model for each asset series, which is turn defines the matrix D_t:

$$h_{it=\omega_i} + \sum_{p=1}^{pi} \alpha ip\, R_{it-p}^2 + \sum_{q=1}^{Qi} \beta iq h_{it-q} \tag{5}$$

There are two essential steps in the DCC-GARCH model estimated process. Univariate GARCH models are estimated in the initial step for every asset series. Equation 5 yields parameters like $\omega_i, \alpha ip\ and\ \beta iq$ that are used to describe the conditional variance of individual assets.

The dynamic correlation parameters are estimated in the second step using the DCC-GARCH model. Equation 4 represents the log-likelihood function (L) of this estimator. The variables in this equation account for the log of the time-varying correlation matrix (R_t), the log of conditional variance (D_t) and the inverse of R_t. The variable "K" indicates the dimension of the data. The log-likelihood function is the foundation for estimating the model's parameters.

3.2.4. Dynamic Correlation Structure (Qt)

The equations define the dynamic correlation structure:

$$Qt = (1 - \sum_{m=1}^{M}\alpha m - \sum_{n=1}^{N}\beta n)\, Q^{-} + \sum_{m=1}^{M}\alpha m\,(\mathcal{E}\,t - m\,\mathcal{E}'t - m) + \sum_{n=1}^{N}\beta n Q\, t - n \tag{6}$$

The evolution of the conditional correlations can be modelled to a time-varying correlation structure, denoted by Q_t (equation 6). where M is the innovation term length, and N is the lagged correlation matrix length, it takes into consideration the impact of previous innovation (Ɛ - $\mathcal{E}t{-}m\mathcal{E}t{-}mT$) and previous lag correlation matrices ($Qt{-}n$).

$$\mathrm{Rt} = \mathrm{Qt} * -1\mathrm{QtQt} * -1 \tag{7}$$

M is the innovation term length, and N is the lagged correlation matrix length. The matrix Qt* is a diagonal matrix comprising the square root of the diagonal elements of Qt, and Q- is the unconditional covariance of the standardized residuals obtained from the first-stage estimation.

$$Q_t^* = \begin{bmatrix} \sqrt{q11} & 0 & 0 & \dots & 0 \\ 0 & \sqrt{q11} & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & \sqrt{qkk} \end{bmatrix} \quad (8)$$

The elements of the matrix Rt are:

$$P_{ij} \equiv \frac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}} \quad (9)$$

There are two parts to the estimating process for the DCC-GARCH model: first, individual GARCH models are estimated for each residual series, which are subsequently utilized to determine the dynamic correlation parameters. The univariate GARCH model parameters for each asset series and the dynamic correlation parameters comprise the two model parameter groups.

3.3. Robustness Check: Wavelet Analysis

Using the Wavelet Coherence method, we examined the empirical outcomes' robustness by examining the association among the financial and COV-19 pandemic variables (i.e., new daily cases). In order to map the series into time and frequency domains and identify both short- and long-term correlations between each wave of COVID-19 daily new cases and the returns of each stock index, wavelet coherency (WC) employed in this work. This study assessed the association among the economic variables KSE100 and KMI30, the COV-19 pandemic variable, and new daily cases. The wavelet coherence method allows us to pinpoint specific areas in the time-frequency domain, as Marwan, Thiel, and Nowaczyk (2002) outlined, wherever significant and notable differences in the co-movement trends in the observed time series occur. According to Torrence and Compo (1998), the factor of the adjusted wavelet coherence can be as follows:

$$W^2_{(s,t)} = \frac{w^2 \mathrm{H}(H^{-1}|N_a(\mathrm{s,t})|2}{\mathrm{H}(\,H^{-1}\,|N_b(\mathrm{s,t})|2} \quad (10)$$

This method improves our understanding of the links between these factors during the COVID-19 pandemic by helping us to recognize and comprehend the interactions and correlations between them at various time scales.

In this case, H stands for the flattening process. The charge of the squared Wavelet Coherence, represented as W^2 (s, t), is between 0 and 1, or 0 ≤ W^2 (s, t) ≤ 1. The squared Wavelet Coherence coefficient range illustrations the unit of correlation between the variables under examination. Below is a display of the Wavelet Coherence phase difference:

$$\emptyset_{xy}\,(s,t) = tan^{-1}\left(\frac{\ell\varkappa\left\{S\left(s^{-1}\,N^{ab}(s,t)\right)\right\}}{W\left\{S\left(s^{-1}\,N^{ab}(s,t)\right)\right\}}\right) \text{ , with } \pm\nexists_{s,t} \in [-\pi,\pi] \quad (11)$$

The symbols denote the imaginary and real components of the smoothed wavelet transform. L$\varkappa$ and Respectively.∅_ (xy) (s, t) ∊ [-п, п] can be calculated using the sign of each component. On the wavelet coherence graphs, black arrows show phases. Time series moving in unison are consistent with a phase difference of zero. Time series that are favorably (negatively) linked or out of phase are shown by arrows pointing to the right or left. Whereas an arrow pointing down indicates that the second time series leads the first by п/2, an arrow pointing upward demonstrates that the first time series leads the second by п/2.

When this coefficient approaches a value near zero, it signifies a lack of correlation or co-movement, indicating that the variables are not moving together. On the other hand, when the coefficient approaches one, a high correlation or co-movement is observed; this can be interpreted as a scale-specific squared correlation between the series. To address the limitations of squared coherence in differentiating between positive and negative correlations, we employ the Monte Carlo method to evaluate the lead/lag relationship between the two series. We can investigate the temporal and direction correlations between series using this method.

3.4. Framework for Theory

3.4.1. Black Swan Theory

In the context of our study, the Black Swan Theory, as pronounced by Nassim Nicholas Taleb Antipova (2020), is invoked to clarify the profound impact of unexpected and rare events on financial markets. With the COVID-19 pandemic serving as an applicable example, the theory highlights the volatility of such occurrences, emphasizing their potential to disturb conventional market expectations. Incorporating the Black Swan Theory into our methodology allows us to detect how the unparalleled nature of the pandemic influences the dynamic correlations between Conventional (KSE100) and Islamic (KMI30) indices, providing valuable insights into market behavior during exceptional events.

4. Results and Discussion

4.1. Descriptive Statistics

Table 1 provides significant descriptive statistics on how the KSE100 and KMI30 indices performed during the COVID-19 pandemic is various waves. This analysis spans the period from March 2020 to August 2022 and is critical for academics and investors seeking to comprehend the complex financial market situation in these historic times. The mean returns, a key criterion for evaluating the performance of these indices, show encouraging trends. While the mean returns of the KSE100 and KMI30 fluctuate over time, wave 2 is notable for its relative profitability, with mean returns of 0.0008. In sharp contrast, wave four is characterized by significant underperformance, with the KSE100 returning -0.0005 on average. The changes is mean returns reflect the dynamic character of financial markets during the pandemic. Further investigation of the data reveals that median returns follow a similar trend. The positive median in wave 2 for both indices indicates moments of relative strength, whilst negative medians in waves 4 and 5 indicate periods of underperformance. This trend highlights the complex and uncertain environment that investors encountered throughout these violent waves. Beyond the central tendency metrics, the standard deviation, a critical volatility indicator, provides interesting information. Notably, KSE100 continuously shows lower volatility than KMI30 in each wave, implying that KSE100 is less vulnerable to market changes; however, waves 1 and 5 show higher standard deviations, indicating increased volatility and market uncertainty.

Wave 3 and 4 have lower standard deviations, indicating more steady returns. These data can help investors develop strategies appropriate for their risk tolerance. Exploring skewness, a measure of return distributions' asymmetry, improves our knowledge of the data. KSE100 shows negative skewness throughout all waves, with wave 1 having the most pronounced left-skewed distribution.

The KSE-100 had a higher frequency of negative returns over these periods, whereas the KMI30 has a skewness value close to zero, indicating a more symmetric distribution with a small quantity of positive bias. The kurtosis analysis, which assesses the shape of the distribution tails, shows that both indices have heavy-tailed distributions, with kurtosis values of more than three, indicating a higher possibility of severe positive or negative returns. Heavy distribution tails might appeal to risk managers and investors who want to account for tail risk in their portfolios.

We use the Jarque-Bera test to investigate the normality of the return distributions, and the results show that both indices deviate from normality in most waves. The higher Jarque-Bera test values and low related probability support the idea that the returns distributions for KSE100 and KMI30 are abnormal. This result has ramifications for typical statistical analysis, forcing researchers and investors to examine alternate methodologies that account for non-normality.

Determining if financial time series data are stationary is critical to evaluating them. The Augmented Dickey-Fuller (ADF) test used for this purpose shows that the KSE100-KMI30 index is stationary at the level in all waves. This stationarity is critical for time series modelling and forecasting because it ensures that the data does not show non-stationary trends, making analysis difficult. The complete descriptive statistics provided a thorough insight into the challenging patterns of COVID-19 instances throughout multiple waves. This investigation spans from March 2020 to August 2022 and is critical for researchers, policymakers, and public health specialists attempting to traverse the complicated landscape of the pandemic's effects. Notably, mean daily new cases vary throughout waves, with Wave 3 demonstrating more significant counts and Wave 5 indicating a time of lower cases, reflecting the pandemic's ever-changing trajectory.

Table 1
Descriptive Statistics for KSE100 and KMI30 Indices Across Five Waves

KSE100	**Wave 1**	**Wave2**	**Wave3**	**Wave4**	**Wave5**
Mean	0.0004	0.0008	0.0004	-0.0005	-0.0003
Median	0.0024	0.0011	0.0001	-0.0006	0.0006
Max	0.0468	0.0344	0.0233	0.0272	0.0375
Min	-0.071	-0.032	-0.024	-0.048	-0.039
Std. D	0.0186	0.0096	0.0094	0.0101	0.0107
Skew	-1.3802	-0.2070	0.0065	-0.5153	-0.5864
Kurt	7.2249	4.4971	3.2649	7.1212	5.0559
JB	129.4718	12.4650	0.2990	80.4556	37.5794
Prob	0.0000	0.0020	0.8611	0.0000	0.0000
ADF	-6.420	-7.756	-7.106	-7.595	-8.941
p-value	0.000	0.000	0.000	0.000	0.000
KMI30					
	Wave 1	Wave2	Wave3	Wave4	Wave5
Mean	0.0004	0.0011	0.0001	-0.0006	-0.0002
Median	0.0012	0.0007	-0.001	-0.0012	0.0006
Max	0.0619	0.0400	0.0287	0.0341	0.0431
Min	-0.078	-0.034	-0.024	-0.058	-0.045
Std. D	0.0223	0.0115	0.0107	0.0121	0.0127
Skew	-0.9290	0.0432	0.1457	-0.5146	-0.6464
Kurt	6.0286	3.7870	3.3348	7.2742	4.8869
JB	64.1743	3.2390	0.8370	86.1691	35.0977
Prob	0.0000	0.1980	0.6580	0.0000	0.0000
ADF	-6.963	-7.972	-7.275	-7.844	-9.106
p-value	0.000	0.000	0.000	0.000	0.000

Note: KSE100 and KMI30 refer to indices measured across five waves. Values shown are mean, median, maximum, minimum, standard deviation (Std. Dev.), skewness, kurtosis, Jarque-Bera statistic (JB), probability associated with JB (Prob), Augmented Dickey-Fuller (ADF) statistic, and associated p-value for each wave.

Similarly, median daily new cases follow these trends, reflecting moments of stability and increasing case counts. The standard deviation data reveal varying levels of volatility, emphasizing the need for flexibility in response strategies. Positive skewness values point to a right-skewed distribution, highlighting the prevalence of lower daily case counts. Moreover, high kurtosis values suggest heavy-tailed distributions, signaling a greater likelihood of extreme case counts. The Jarque-Bera test results confirm the non-normality of the distribution, reinforcing the irregular and non-random nature of the pandemic's impact.

The descriptive statistics for each wave's new daily cases are displayed in Table 2. The highest mean is indicated in Wave 3, with a mean value ranging from 5.067 to 11.626 patients per day. Wave 5 displays the most elevated standard deviations, with an average range of daily COVID-19 case rates of 3.807–7.679. The skewed results show that the distribution of COVID-19 instances is positively skewed, meaning that more values fall on the positive side. Higher kurtosis levels indicate more severe values in the tails. Positive kurtosis in all waves indicates comparatively heavy tails compared to a normal distribution. Positive kurtosis levels also suggest more severe values in the bottoms. The ADF test has confirmed that the data is stationary. Initial differencing (I) has been applied in every wave, indicating that the COVID-19 cases become stationary after this transformation (Shaturaev, 2023).

In line with the comprehensive report by Noreen et al. (2020), it is notable that Pakistan confronted its initial significant surge of COVID-19 infections, registering 134 confirmed cases on March 17, 2020. The implications of this pivotal moment reverberated throughout the financial landscape; a phenomenon intensely depicted in Figure 1. This visual representation displays a substantial spike in the waves, especially in Wave 1 (W1), primarily attributed to the highest single-day surge in new COVID-19 cases, peaking at 6,825 on June 14, 2020. Figure 2, an instrumental component of the report, unveils a compelling pattern within the trends of return indices during the tumultuous waves of the pandemic. Initially, these indices experienced a synchronized decline, emblematic of the challenges posed by the unprecedented COVID-19 crisis. Significantly, the sharpest declines in share returns coincided with the peak of the crisis, highlighting the profound impact of the pandemic on financial markets. However, as global COVID-19 cases gradually declined and economies cautiously embarked on reopening a noteworthy transformation took place. The rise in interest rates, the drop in the price of oil, and the start of the Coronavirus were the fundamental causes of the stock market losses. Millions of rupees invested in various shares saw their value cut by a third and, in some cases, by half.

Table 2
Descriptive Statistics

New-Daily-Cases	Wave1	Wave2	Wave3	Wave4	Wave5
Mean	6.959	6.584	11.626	7.781	5.065
Median	3.740	5.878	10.291	3.961	2.079
Max	27.704	13.830	24.145	20.320	30.523
Min	0.001	1.477	3.664	1.048	0.000
Std. Dev.	7.159	3.807	6.360	6.889	7.679
Skew	1.113	0.278	0.513	0.552	2.068
Kurt	3.138	1.706	1.880	1.621	6.230
J-B	25.267	10.250	9.807	13.916	184.744
Pro	0.000	0.006	0.007	0.001	0.000
ADF I(1)	-6.462	-4.570	-4.602	-6.998	-3.381
Pro	0.000	0.000	0.000	0.000	0.013

Note: Table 2 contains descriptive statistics for new daily cases of COVID-19. Jarque-Bera test of normality and augmented Dickey-Fuller (ADF) stationarity test, respectively. A 1% significance level indicates rejection of the null hypothesis of normalcy and the unit.

The graph displays the movements of the Karachi stock markets (KSE-100 Index and KMI-30). An increase was anticipated, but the COVID-19 outbreak caused panic, which intensified when the lockdown was declared in the middle of March 2020. It took nearly a year to return to the same level, even though it had begun to do so by the end of March. Notably, a consistent pattern emerges whenever there is a surge in COVID-19 cases. It tends to align with subsequent decreases in KSE100-KMI30 stock prices. This analysis reinforces the idea that each wave of the COVID-19 pandemic distinctly influences the performance of the KSE100-KMI30 indices, aligning with the study's findings (Ghouse et al., 2023).

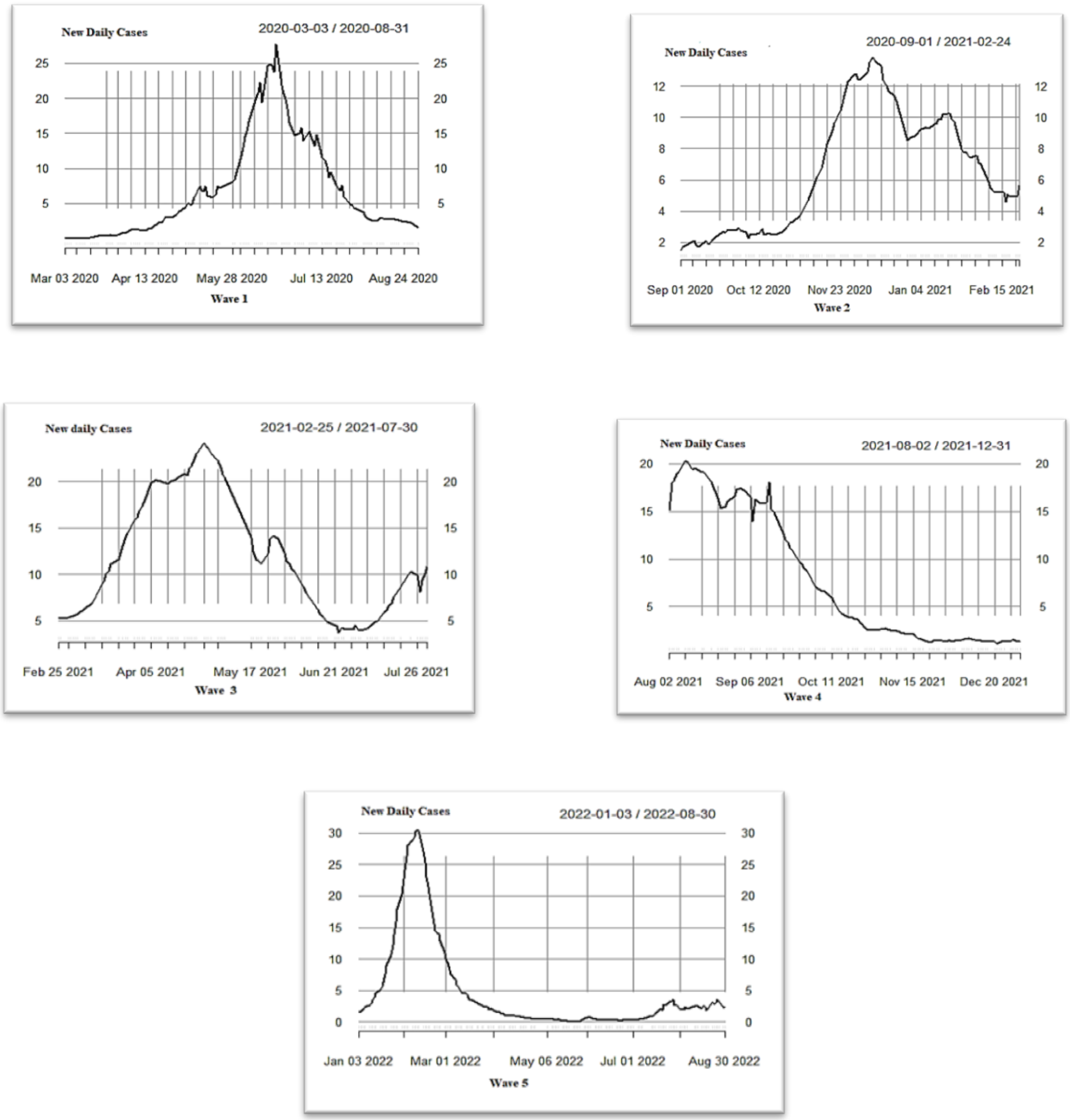

Figure 3: Visualization of New Daily Cases of COVID-19

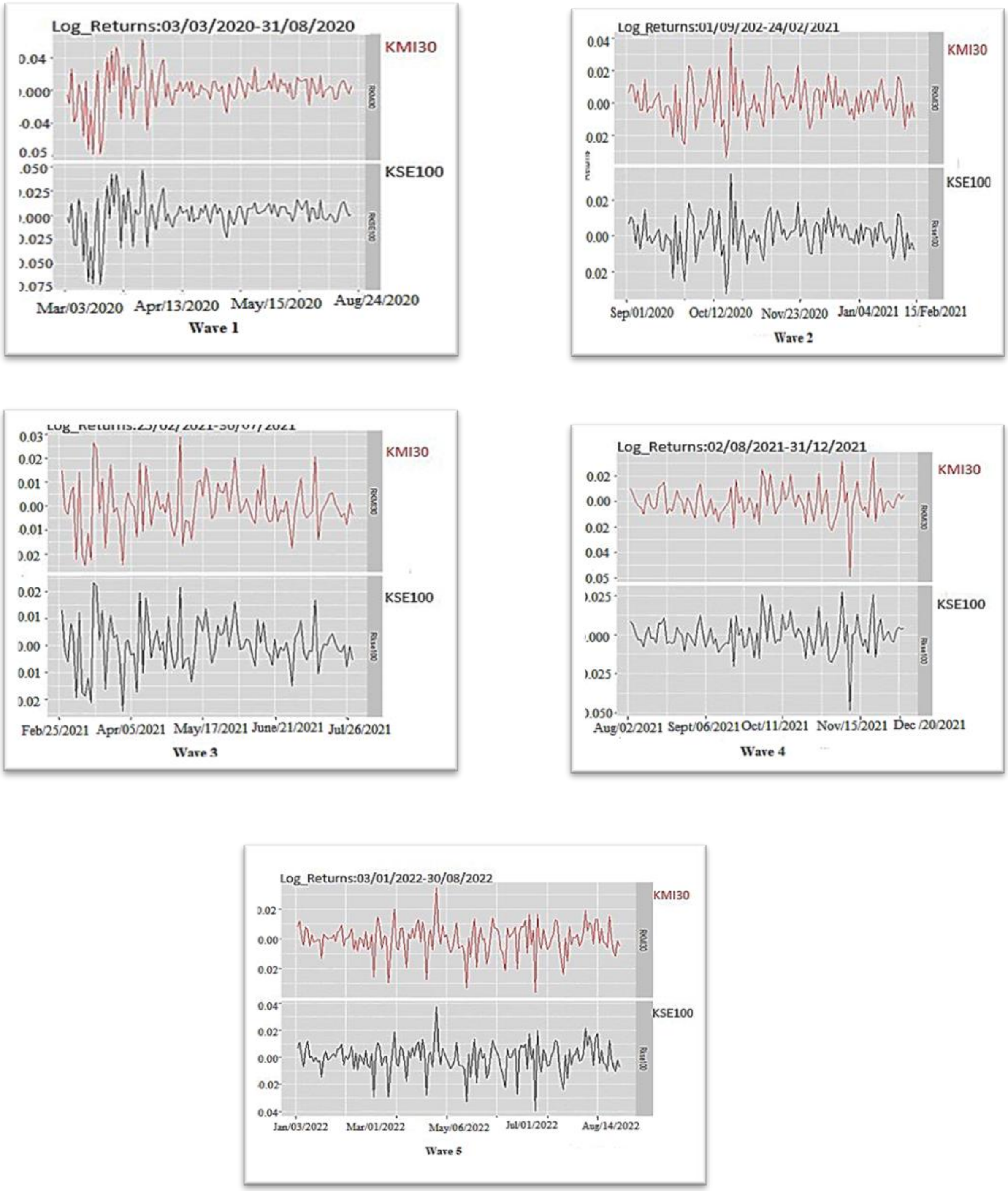

Figure 4: Visualization of Daily Returns of KSE100 and KMI30 indices

4.2. DCC GARCH Model Analysis

4.2.1. DCC GARCH Model Analysis: Dynamic Conditional Correlation KSE100&KMI30 indices with new daily cases of COVID-19

First, we analyze the dynamic linkage between COVID-19 new daily cases with both conventional and Islamic indices of PSX during each wave. After that, we analyze the dynamic linkage between both indexes and see how the time of volatility correlates.

We employ the DCC (Dynamic Conditional Correlation) process to estimate correlation coefficients between the Islamic KMI30 index, the conventional KSE100 index, and the daily COVID-19 cases to compare different pandemic phases, as outlined in Table 3. Our analysis aims to evaluate and differentiate the correlation duration between these pairs throughout each phase of the pandemic.

Table 3
DCC Parameters between PSX Index and New Daily Cases of Pakistan

COVID-19 cases with KSE100					
	wave 1	**wave 2**	**wave 3**	**wave 4**	**wave 5**
a^{DCC} Coef.	0.000	0.000	0.000	0.000	0.000
a^{DCC} Prob.	0.990	0.999	0.977	0.999	0.998
b^{DCC}	0.914	0.929	0.914	0.930	0.918
b^{DCC} Prob.	0.001	0.000	0.000	0.000	0.000
a+b	0.914	0.9291	0.9144	0.930	0.918
COVID-19 cases with KMI30					
	wave 1	**wave 2**	**wave 3**	**wave 4**	**wave 5**
a^{DCC} Coef.	0.0192	0.000	0.000	0.000	0.000
a^{DCC} Prob.	0.663	0.999	0.991	0.821	0.998
b^{DCC} Coef.	0.883	0.929	0.916	0.930	0.917
b^{DCC} Prob	0.000	0.000	0.000	0.000	0.000
a+b	0.883	0.929	0.9163	0.930	0.9176

Note: DCC parameters (a DCC and b DCC) represent coefficients and associated probabilities (Prob.) between the PSX indices (KSE100 and KMI30) and new daily cases of COVID-19 across five waves

Table 3 presents the results of the DCC GARCH analysis conducted between the PSX indices and the daily new COVID-19 cases for each wave. In this analysis, a ^{DCC} parameter captures the market shocks' impact on conditional correlations, while b^{DCC} signifies the long-term persistence of these conditional correlations. Notably, both parameters exhibit positive values; however, only the b^{DCC} parameters achieve statistical significance. These results indicate that the degree of persistence in the correlations is notably high, and historical market shocks do not significantly influence conditional correlations. Ultimately, our findings validate the long-term correlation between each wave's COVID-19 instances and PSX indices. The significance of b^{DCC} in each wave suggests that one variable's volatility affects the other's volatility, implying that extreme or uncertain events associated with COVID-19 have a notable impact on stock market volatility.

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4.2.2. Dynamic Conditional Correlations Visualization: Cases-KSE100 & KMI30

In Figs., we exhibit the dynamic co-movements of the conditional correlations during the sample period. 3 (1–5) and 4(1–5) to provide a visual idea of the dynamic behaviour of the relationship between the COVID-19 daily cases and KSE100 and KMI30 indices. The picture illustrates the weakly negative co-movements in all waves of the dynamic connection between stock returns and coronavirus illnesses, except wave 4 exhibits a weak but positive co-movement. It implies that the relationship between COVID-19 cases and both indices of PSX is not very strong; the correlation coefficient is close to zero. This plot suggests that, on average, both indexes tend to have a weak negative correlation with COVID-19 cases. As COVID-19 cases increase, the index tends to decrease slightly, but in wave 4, both indices move in the same direction with COVID-19 cases. This result suggests a downward trend in stock returns when more coronavirus infection cases are found. The results align with research that shows pandemics have a detrimental impact on stock market performance. This finding defies assumption because bad news is typically linked to a fall in stock market returns.

4.2.3. Dynamic Conditional Correlation between KSE100 & KMI30 Indices in each Wave

To examine the evolving dynamics of co-movement between the KSE100 and KMI30 within Pakistan's stock markets throughout the global health crisis, from March 3, 2020, to August 30, 2022, we employed the DCC-GARCH (1, 1) methodology. This approach, which allows for the adjustment of conditional volatility and correlations over time, is a pivotal tool for elucidating the dynamic behaviour of stock markets. The results obtained from the DCC-GARCH (1, 1) model are presented in Table 4.

Table 4 summarizes the findings of a dynamic conditional correlation research conducted between the PSX Islamic (KMI-30) and conventional (KSE-100) indices during different pandemic generations. In waves 1 and 2, the estimated parameters (α_{kse100}, α_{kmi30}) are significantly positive, indicating that conditional variance of returns is influenced by past innovation (shocks); it suggests that in this wave, COVID-19 impact on volatility and in both waves, GARCH parameters (β_{kse100}, β_{kmi30}) are statistically significant indicating that past conditional variance influence current conditional variance, there is persistence of volatility.

In the second step, we estimate DCC model parameters using standardized residuals obtained from the first step. The results are presented in Table 4. In the context of waves 1 and 2, a ^{DCC} parameter reflects the influence of sudden market shocks on conditional correlations, while b^{DCC} characterizes persistence in the conditional correlation. In wave 1, parameters a DCC and b^{DCC} are positively significant, indicating the impact of past market shocks and persistence on conditional correlations. In wave 2, however, both parameters remain positive; only bDCC reaching statistical significance suggests that past conditional correlation contributes to the current conditional correlation. It is worth highlighting that b^{DCC} surpasses a^{DCC} in both waves, indicating that the behaviour of current variance is more affected by the magnitude of past variance than by past innovations. The combined sum of DCC parameters (a^{DCC} + b^{DCC}) is greater than zero, indicating that the conditional correlation between series is not constant (Yousfi et al., 2021).

In waves 3, 4, and 5, ARCH parameters (α_{kse100}, α_{kmi30}) demonstrate statistical significance only in the context of KMI-30 during wave four, indicating that conditional variance of returns is influenced by past innovation (shocks) only in KMI-30 of wave 4. Meanwhile, the estimates of the β parameter in waves 3, 4, and 5 exhibit significances at a 1% level across both series; GARCH parameters (β_{kse100}, β_{kmi30}) are statistically significant, indicating that past conditional variance influences current conditional variance, there is persistence of volatility. Notably, this persistence is particularly pronounced in the cases of KMI30 and KSE100 during waves 3, 4, and 5. It is worth noting that the β parameter reveals the presence of enduring characteristics in volatility clustering, with a higher degree of persistence observed in KMI30 during waves 3 and 4. In contrast, during wave 5, KSE100 exhibits more stability. The sum of coefficients of α+ β parameters persistence in waves 3, 4, and 5 are below one unit. This observation implies that the impact of volatility is more noticeable over the long term than in the short term. The statistical significance observed in both short- and long-term contexts offers empirical support for the volatility-clustering phenomenon. In the subsequent step, we estimate the parameters of the DCC model. In waves 3, 4, and 5, the a^{DCC} parameter reflects the impact of shocks on conditional correlations, while b^{DCC} characterizes the persistence of these correlations. However, both parameters are positive and achieve statistical significance during waves 4 and 5. These results underscore the high degree of persistence in correlations and the enduring influence of past market shocks on conditional correlations.

Nevertheless, both parameters exhibit positivity in wave three, with only the b^{DCC} parameters attaining statistical significance. Additionally, we observe that b^{DCC} consistently surpasses a^{DCC} in both waves, which leads us to argue that the influence of current variances is more affected by the magnitude of past fluctuations than prior innovations. The sum of DCC parameters (a^{DCC} + b^{DCC}) exceeds zero, indicating that conditional correlations between conventional and Islamic indices remain dynamic and not constant (ERDOĞAN et al., 2020; Hasan et al., 2021b; Nabi et al., n.d.). The "Standardized Residuals Diagnostics" section's p-values for Q and Q^2 statistics indicate no appreciable ARCH effects in residuals across waves. Based on the ARCH-LM test and Ljung-Box Q2 statistics, the estimated models meet the requirements of the GARCH theory in terms of the diagnostic fit shown in Table 4 (Jabeen & Kausar, 2021).

4.2.4. Dynamic Conditional Correlations Visualization: KSE100-KMI30

We maintain a fixed estimation window across all waves to establish dynamic conditional correlations between the KSE100 and KMI30 indices in the Pakistan stock market. The number of observations in each wave determines this window: the first wave consists of 122 observations, the second wave has 124 observations, the third wave comprises 102 observations, the fourth wave has 107 observations, and the fifth wave contains 161 observations. Given the inherently dynamic relationship between KSE100 and KMI30, our research delves into this market pair's Time-Varying Dynamic Conditional Correlation during the COVID-19 pandemic. The findings are unfilled in Figure 5 (a-e). The graph shows that both indices are highly positively correlated in each wave. A correlation coefficient close to one (in this case, ranging from 0.80 to 0.99) indicates a strong positive correlation between KSE100 and KMI30. The substantial interconnection observed between the Sharia-compliant and traditional indexes within each market wave highlights a significant level of co-movement and a consistently positive correlation between these indices in the Pakistani stock market. This correlation is notable, especially considering that the Sharia-compliant index is a subset of the conventional index, leading to predictable outcomes. Despite the assumption that the Sharia-compliant index, as a subset, might act as a haven, the research suggests otherwise.

Table 4a
DCC GARCH Estimation

Wave 1							
Parameters	**α (KSE100)**	**α(KMI30)**	**β (KSe100)**	**β(KMI30)**	**a^{DCC}**	**b^{DCC}**	**(a +b)**
Coefficients	0.194846	0.16939	0.778636	0.798938	0.0687	0.9041	**0.9727**
t-statistic	2.69025	2.62649	13.45796	14.63212	2.9401	25.56	
P-value	0.00714	0.008627	0.000	0.000	0.0033	0.000	
Standardized Residuals Diagnostics						**ARCH Effect**	
	Q(KSE100)	**Q^2(KSE100)**	**Q(KMI30)**	**Q^2(KMI30)**		**KSE100**	**KMI30**
Statistic	1.778762	7.9831	1.83288	4.394		2.377	1.941
p-value	0.7739	0.12987	0.7588	0.5234		0.1231	0.1636
Wave 2							
Estimation of DCC-GARCH (1,1) Model parameters							
Parameters	**α (KSE100)**	**α(KMI30)**	**β (KSe100)**	**β(KMI30)**	**a^{DCC}**	**b^{DCC}**	**(a+ b)**
Coefficients	0.179481	0.242726	0.64471	0.582877	0.0116	0.95	**0.9616**
t-statistic	2.2574	2.1089	5.7701	3.8501	0.3411	5.251	
P-value	0.023981	0.034951	0.000	0.000118	0.733	0.000	
Standardized Residuals Diagnostics						**ARCH Effect**	
	Q(KSE100)	**Q^2(KSE100)**	**Q(KMI30)**	**Q^2(KMI30)**		**KSE100**	**KMI30**
Statistic	1.5777	6.6282	2.2397	8.125		1.698546	1.5337
p-value	0.8273	0.2323	0.6416	0.1218		0.5417	0.5835

Note: Table 4 Estimation of DCC-GARCH (1, 1) Model parameters (KSE100, KMI30)

Investors are unlikely to benefit from seeking refuge in a haven or employing hedging strategies based on the Sharia-compliant stock index. Contrary to expectations, the Sharia-compliant indices are found to be susceptible to financial crises, such as the impact of COVID-19, similar to their conventional counterparts. Recent research emphasizes that the Shariah-compliant screening procedure applied to the Islamic index does not protect against sudden market shocks triggered by events like the COVID-19 pandemic. Instead, Sharia-compliant indices exhibit reactions comparable to their conventional counterparts during such crises, as evidenced by studies (Aliani et al., 2022; Elshqirat, 2021; Hasan et al., 2021; Yousfi et al., 2021). This underscores the need for investors to reassess assumptions regarding the resilience of Sharia-compliant indices in the face of unforeseen market disruptions.

Table 4b
DCC GARCH Estimation

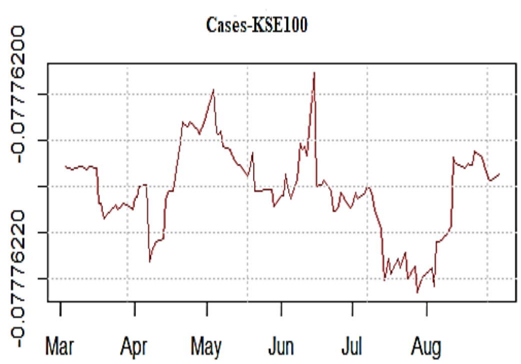
Wave 3							
Estimation of DCC-GARCH (1,1) Model parameters							
Parameters	**α (KSE100)**	**α(KMI30)**	**β (KSe100)**	**β(KMI30)**	**a^{DCC}**	**b^{DCC}**	**(a +b)**
Coefficients	0.05128	0.031137	0.931465	0.957985	0.0516	0.762	**0.8136**
t-statistic	0.848375	0.649268	15.663828	19.58733	1.3264	6.557	
P-value	0.39623	0.51616	0.000	0.000	0.1847	0.000	
Standardized Residuals Diagnostics						**ARCH Effect**	
	Q(KSE100)	**Q^2(KSE100)**	**Q(KMI30)**	**Q^2(KMI30)**		**KSE100**	**KMI30**
Statistic	0.938765	1.7835	1.232231	3.571		0.9295	0.6159
p-value	0.9556	0.9292	0.9063	0.6622		0.754	0.849
Wave 4							
Estimation of DCC-GARCH (1,1) Model parameters							
Parameters	**α (KSE100)**	**α(KMI30)**	**β (KSe100)**	**β(KMI30)**	**a^{DCC}**	**b^{DCC}**	**(a+ b)**
Coefficients	0.229641	0.174883	0.748727	0.786691	0.0614	0.914	**0.9754**
t-statistic	1.140465	3.4865	5.497162	10.43598	2.4473	61.52	
P-value	0.25409	0.000489	0.000	0.000	0.0144	0.000	
Standardized Residuals Diagnostics						**ARCH Effect**	
	Q(KSE100)	**Q^2(KSE100)**	**Q(KMI30)**	**Q^2(KMI30)**		**KSE100**	**KMI30**
Statistic	1.01591	7.1238	1.91756	5.4009		5.722	4.107
p-value	0.9444	0.189	0.735	0.373		0.06982	0.1645

Note: Table 4 Estimation of DCC-GARCH (1, 1) Model parameters (KSE100, KMI30)

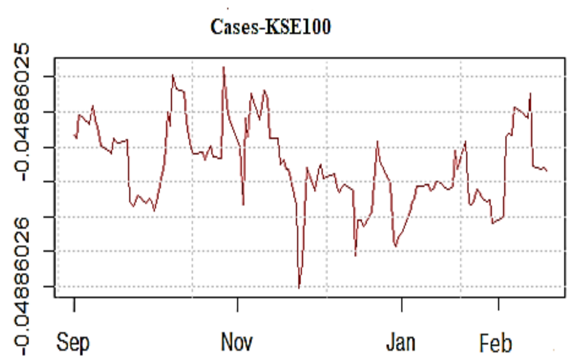
Table 4c
DCC GARCH Estimation

Wave 5							
Estimation of DCC-GARCH (1,1) Model parameters							
Parameters	**α (KSE100)**	**α(KMI30)**	**β (KSe100)**	**β(KMI30)**	**a^{DCC}**	**b^{DCC}**	**(a+ b)**
Coefficients	0.0000	0.048026	0.999	0.950974	0.0308	**0.969**	**0.9998**
t-statistic	0.000006	1.227466	60.516928	19.28218	2.0469	49.32	
P-value	0.999995	0.219647	0.000	0.000	0.0407	0.000	
Standardized Residuals Diagnostics						**ARCH Effect**	
	Q(KSE100)	**Q^2(KSE100)**	**Q(KMI30)**	**Q^2(KMI30)**		**KSE100**	**KMI30**
Statistic	0.72845	2.3708	1.137099	3.281		1.199048	1.5252
p-value	0.9791	0.8564	0.9243	0.7118		0.6749	0.5857

Note: Table 4 Estimation of DCC-GARCH (1, 1) Model parameters (KSE100, KMI30)



Wave 1



Wave 2

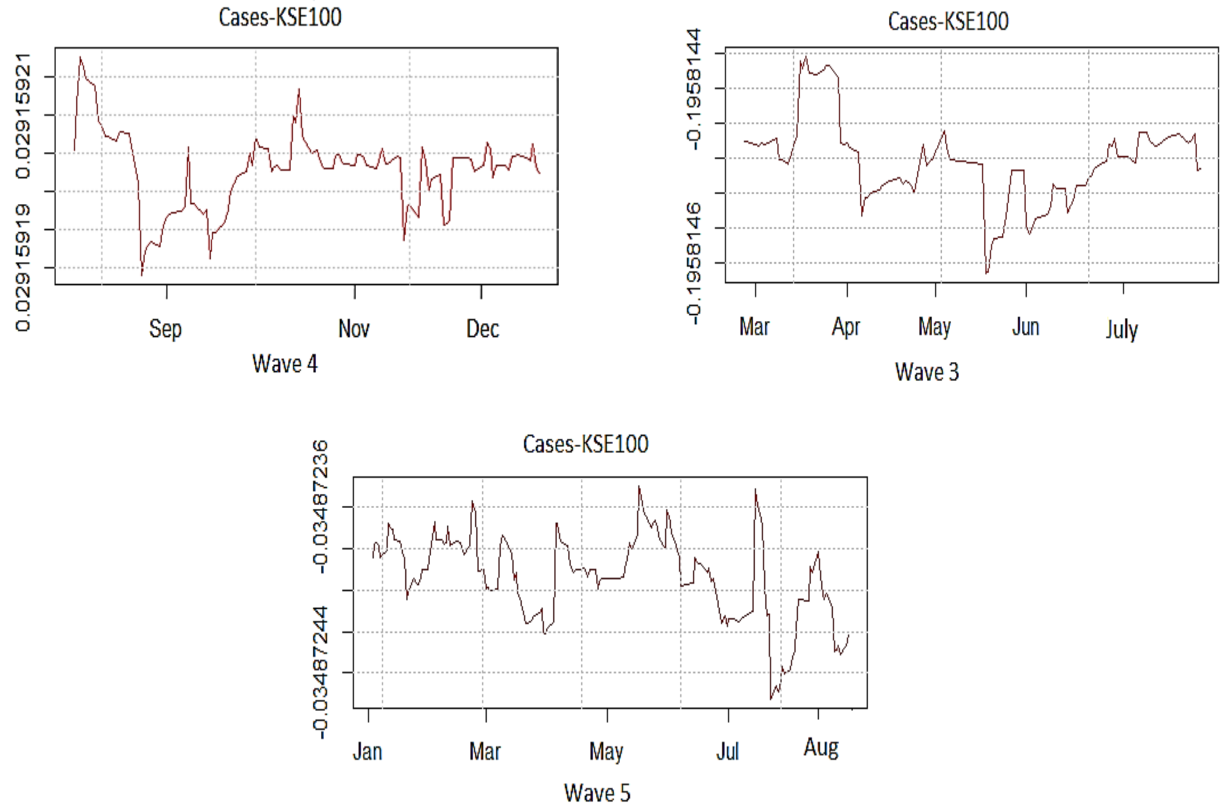
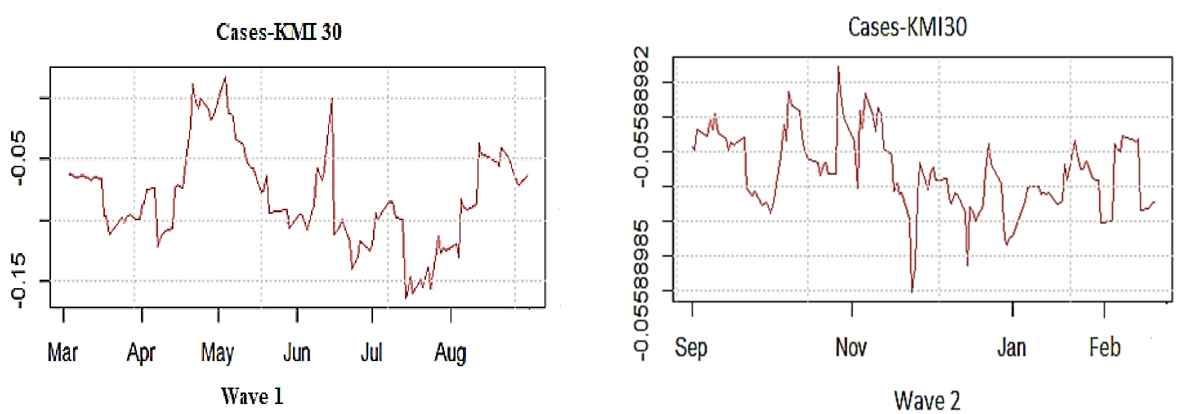


Figure 5: DCC- GARCH Conditional Correlation Visualization: Cases-KSE100 in Waves



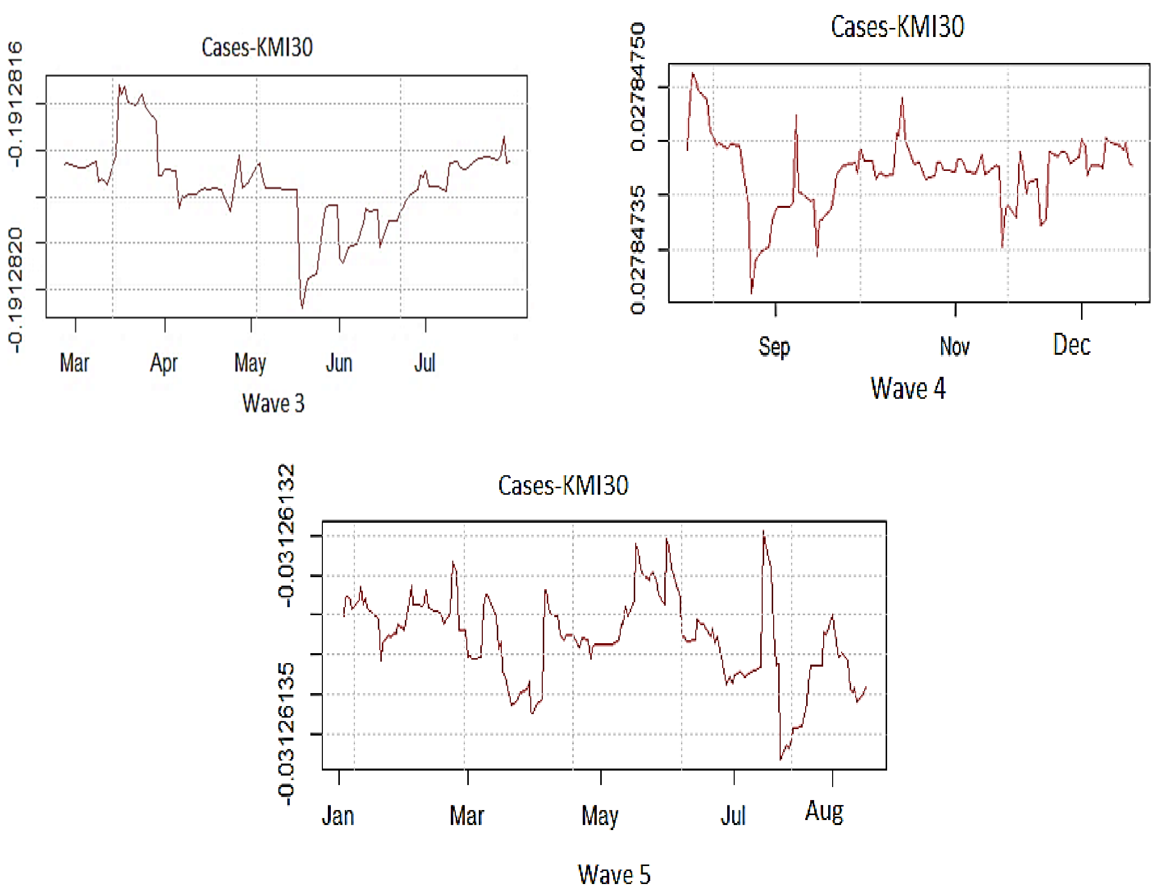


Figure 6: DCC- GARCH Conditional Correlation Visualization: Cases-KMI30 in Waves

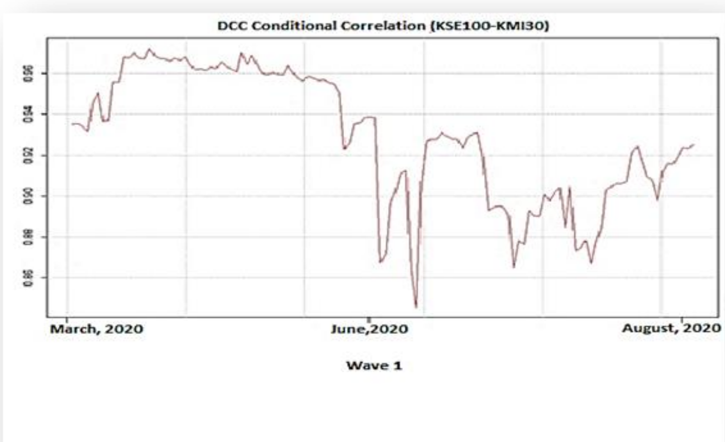


Figure 7.1 : DCC- GARCH conditional correlation (KSE-KMI30) wave 1

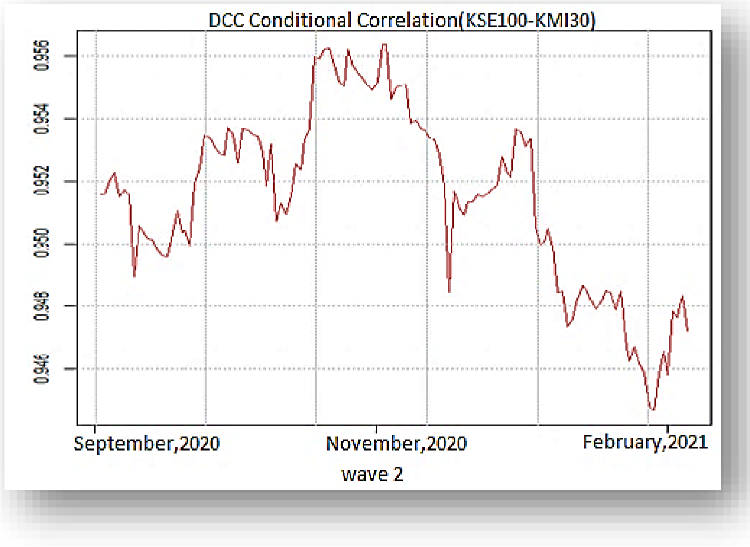


Figure 7.2: DCC- GARCH Conditional Correlation (KSE100-KMI30) Wave 2

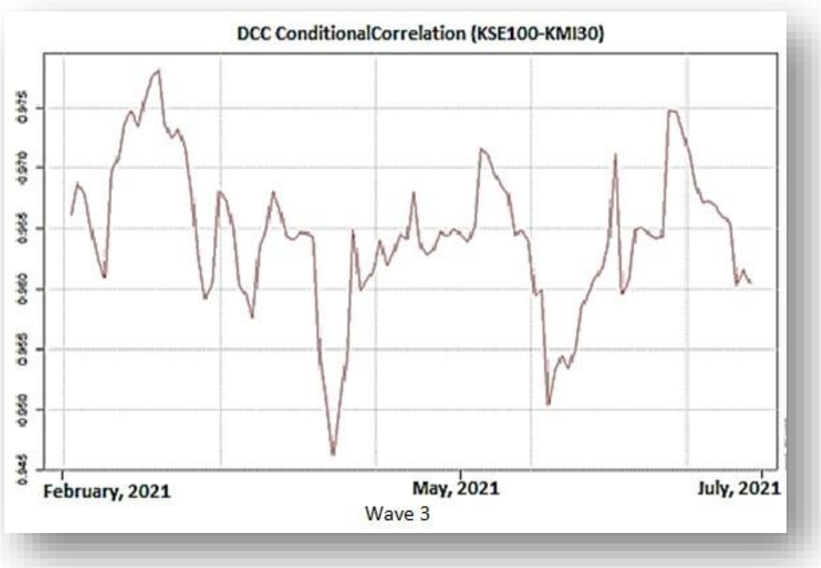


Figure 7.3: DCC- GARCH Conditional Correlation (KSE100-KMI30) Wave 3

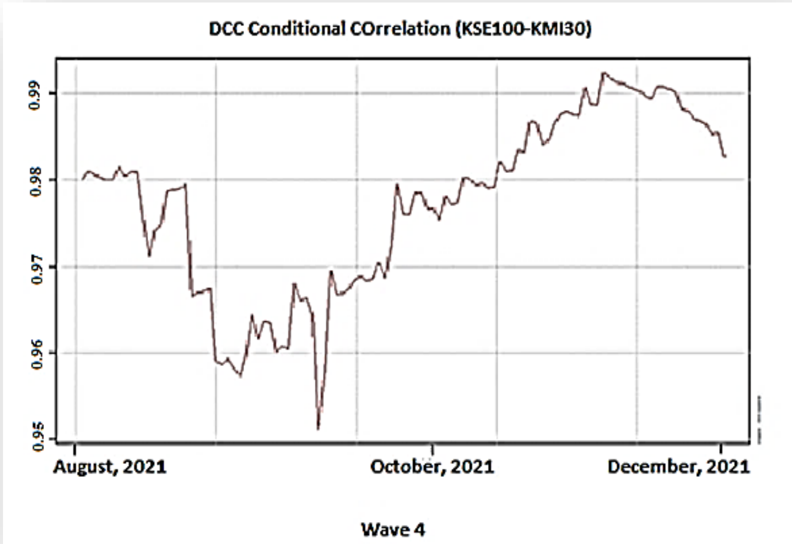


Figure 7.4: DCC- GARCH Conditional Correlation (KSE100-KMI30) Wave 4

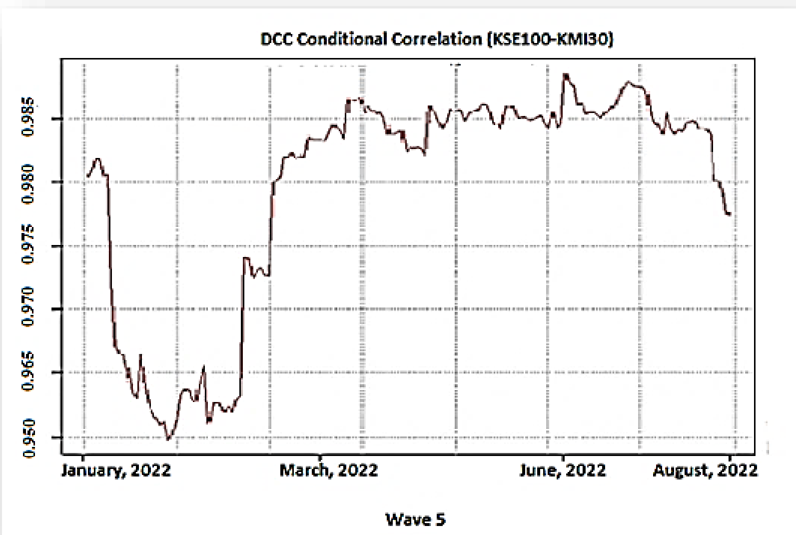


Figure 7.5: DCC- GARCH Conditional Correlation (KSE100-KMI30) Wave 5

5. Robustness check:
5.1. wavelet Coherence analysis

We examined the wavelet coherence between the daily COVID-19 case count and the financial index performance, KSE100 and KMI30, during different COVID-19 pandemic phases. The goal was to evaluate these factors' degree of interdependence and correlation. Wavelet coherence plots were created as visual representations of this investigation, shown in Figure

8.1 to 8.10. The directional arrows in the plots effectively illustrate the outcomes of the wavelet coherence approach, depicting the comparative phasing of the variables under consideration. Blue or cool colours represent regions exhibiting weak co-movements, while areas demonstrating significant correlation are displayed in red or warm colours to indicate significance levels. The arrows' orientations convey the nature of causality and dependency interactions: a leftward arrow indicates a negative connection between the two variables, while a rightward arrow suggests a favorable correlation. In terms of temporal relationships, up right and down-left (↗↙) arrows signify that the first variable leads the second, whereas downright and up-left (↘↖) indicators indicate that the second variable leads the first. The directional arrows, such as up (↑) and down (↓), further signify whether a variable is leading or lagging in the analysis. It is important to note that the rephrasing aims to convey the original message in a plagiarism-free manner.

Figures (8.1 to 8.10) present the outcomes regarding the coherency and phase between new daily Cases, acting as a proxy for COVID pandemic waves and both stock indices. Many small islands suggest a substantial reliance across frequency bands at the first wave period's start, middle, and end. In Figure 8.1, a notable high coherence pocket emerges in the middle of June 2020, spanning over eight days. Within the figure, the arrows are oriented in the left-down direction (↙), signifying an anti-phase relationship. It implies a negative correlation in terms of causality, indicating that new cases influence changes in the KSE100 index. At the peak of new instances, there is a discernible decline in the trend of the KSE100 index, suggesting that as the number of cases increases, this stock index tends to decrease. These results confirm the persistence suggested by b^{DCC} and provide additional information about the anti-phase relationship and the direction of correlation changes.

In Fig.8.2, the high coherence pocket located in 0-4 days during March 2020, where arrows are pointing toward *right-up* ↗ indicating in-phase relationship having a positive correlation regarding causality new-cases leads KMI-30 index. There is a high coherence pocket located in 8 days during Mid-June 2020, where arrows are pointing toward *right-up* ↗ indicating an in-phase relationship having a positive correlation in terms of causality new-cases leads KMI-30 index. There is a high coherence pocket located in 0-4 days during August 2020, where most of the arrows are pointing toward *right-up* ↗ indicating an in-phase relationship having a positive correlation in terms of causality new-cases leads KMI-30 index. In Fig.8.3 high coherence pocket located during Nov-Dec 2020 in 0-8 days, arrows are pointing to *left-up* ↖ indicating an anti-phase relationship suggesting negative correlation in terms of causality KSE100 index leading new-cases suggesting that returns are increasing and new-cases are decreasing. There is a short-lived pocket of high coherence during Jan 2021, where arrows point toward the right, indicating a positive correlation between both variables moving in the same direction. In Fig.8.4 is a high coherence pocket located in 8-16 days during Nov 2020, where arrows are pointing toward *right-up* ↗ indicating in-phase relationship having a positive correlation in terms of causality new-cases leads KMI-30 index (Samadi et al., 2021).

In Fig.8.5, high coherence pocket located during Mar 2021 in 4-8 days, arrows are pointing to *left-down* ↙ indicating anti-phase relationship suggesting negative correlation in terms of causality new-cases leading to KSE100 index, start of 2021 new cases again start to increase, they affect index they start to decline that time their trend of KSE100 index shows a decline. A high coherence pocket is located during June 2021 in 4-8 days; arrows point to *left-down* ↙ indicating an anti-phase relationship, suggesting a negative correlation in causality new-cases leading to the KSE100 index, in Fig.8.6, The high coherency pocket appears out of the cone of influence, suggesting insignificance between the new cases and the KMI30 index; the trend indicates that new cases and KMI30 illustrate low synchronization, as there is absence of any high coherency pocket during the sample period.

In Fig.8.7 , a high coherence pocket located during mid-Nov 2021 in 4-8 days, arrows point to *left-down* ↙ indicating an anti-phase relationship suggesting negative correlation regarding causality new-cases leading KSE100 index, cases increase at that days kse100 sock goes down at those days it means that COVID-19 circumstances affect the conventional index of PSX. There is a short-lived pocket of high coherence during Oct 2021, where arrows are pointing toward *right-up* ↗ indicating in-phase relationship having a positive correlation in terms of causality new-cases leads KSE-100 index. Fig.8.8 is a high coherence pocket located in 8 days during Sept 2021, where arrows point to the *Right-down*↘ indicating an In-phase relationship suggesting a positive correlation regarding causality KMI-30 index leading new-cases.

In Fig.8.9, the high coherence pocket located during March and May 2022 in 0-4 days, *Right-up* ↗ indicating the In-phase relationship having a positive correlation in terms of causality new-cases leads KSE-100 index. Fig.8.10 high coherence pocket located during March 2022 in 4-8 days, *Right-up*↗ indicating In-phase relationship having a positive correlation in terms of causality new-cases leads KMI30-100 index. A high coherence pocket located during mid-March 2022 in 8-16 days *right-down* arrows indicating in-phase relationship having a negative correlation in terms of causality KMI30-100 index leads new-cases (Aliani et al., 2022; Sattar & Siddiqui, 2021; Yousfi et al., 2021).

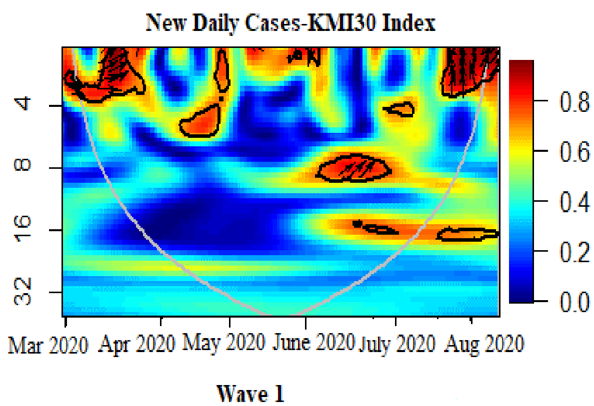


Figure 8.1: New Daily cases-KMI30 (wave1)

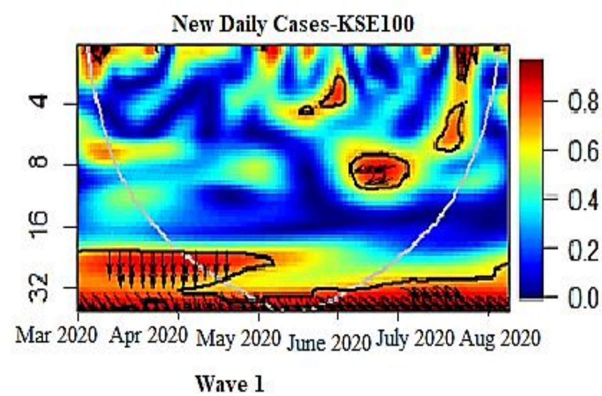


Figure 8.2: New Daily cases-KSE100 (wave1)

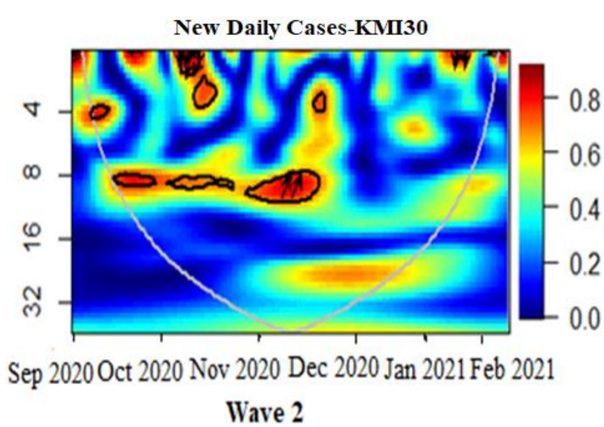


Figure 8.3: New Daily cases-KSE100 (wave2)

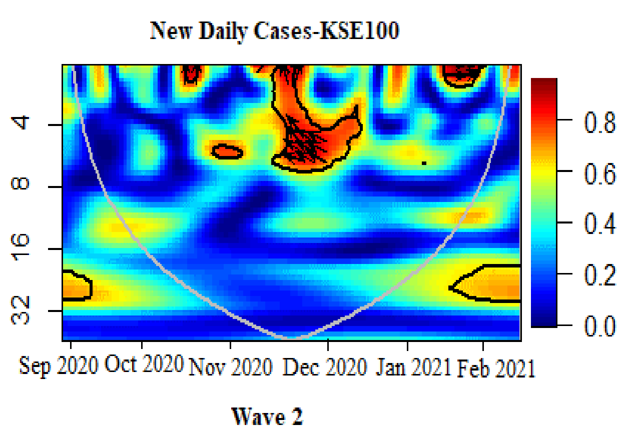


Figure 8.4: New Daily cases-KMI30 (wave2)

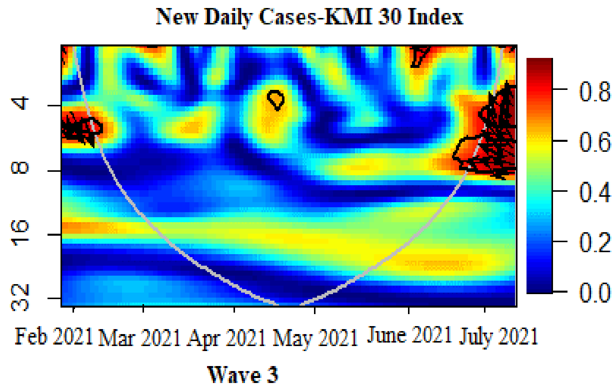


Figure 8.5: New Daily cases-KSE100 (wave3)

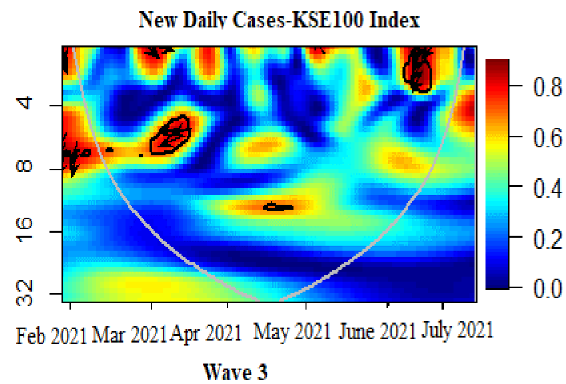


Figure8.6: New Daily cases-KMI30 (wave3)

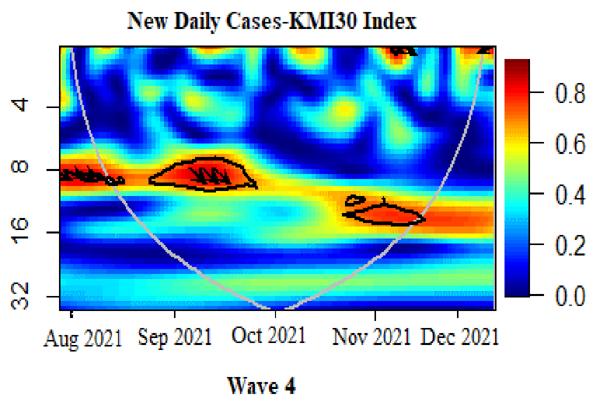


Figure 8.7: New Daily cases-KMI30 (wave4)

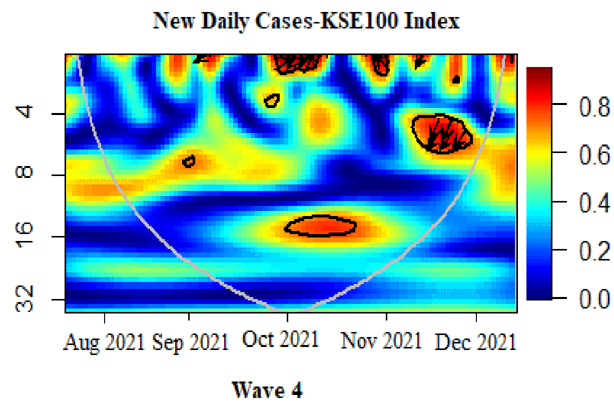


Figure 8.8: New Daily cases-KSE100 (wave3)

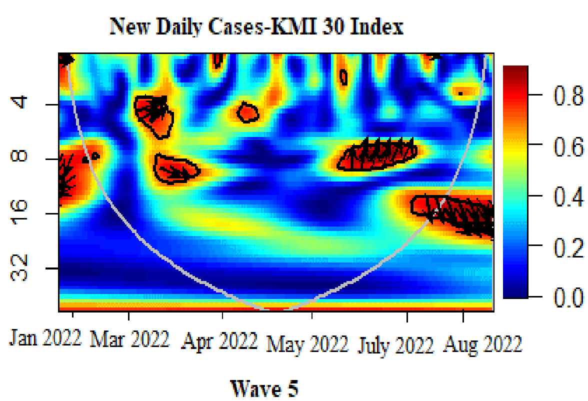


Figure 8.9: New Daily cases-KMI30 (wave5)

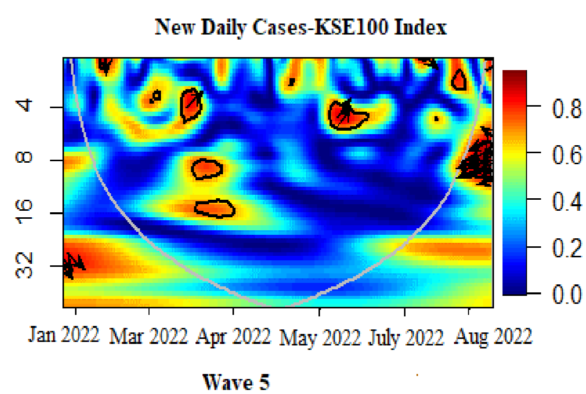


Figure 8.10: New Daily cases-KSE100 (wave5)

6. Conclusion and Policy Implication:
6.1. Research Findings

Our research goals are to illuminate the influence of the epidemic on the (KSE-100) and (KMI-30) indices across its five waves. Over the period spanning from March 3, 2020, to August 30, 2022, we investigated the dynamic relationship between the PSX indices (KSE-100, KMI-30) and the incidence of new COVID-19 cases. To accomplish our goal, we used the DCC GARCH model. This study reveals persistent and significant dynamic conditional correlations between conventional (KSE100) and Islamic (KMI30) indices during distinct COVID-19 waves, emphasizing enduring volatility clustering and supporting contagion effects. Additionally, correlations with daily COVID-19 cases show notable persistence, indicating a significant impact of pandemic-related uncertainties on stock market volatility. The weak negative correlation between stock returns and COVID-19 cases implies a subtle market impact. At the same time, the anomalous positive co-movement in Wave 4 warrants focused policymaker attention for adaptive strategies and risk mitigation. The wavelet coherence analysis reveals dynamic relationships between daily COVID-19 cases and stock indices (KSE100 and KMI30), showcasing varying degrees of correlation and causality across pandemic phases. These findings underscore the need for adaptive risk management strategies, considering the nuanced interplay between health crisis dynamics and financial market behaviour for informed decision-making.

6.2. Sharia-Compliant vs. Non-Sharia-Compliant Indices

The study examines the dynamic conditional correlation between Sharia-compliant and non-Sharia-compliant stock indices during various pandemic waves, explicitly focusing on the uncertainty generated by the sudden panic caused by the global pandemic. The results reveal a substantial correlation, a tendency for Pakistan's screened and non-screened stock market indices to move in tandem throughout each pandemic wave. Despite adhering to specific ethical criteria, the research suggests that screened stock markets are not immune to financial disasters as if COVID-19. Investors may not find screened stock markets effective for hedging or as a safe haven during crises. The study indicates that the distinctive characteristics of screened stocks do not provide superior investment options or hedging opportunities during times of crisis. Therefore, it recommended for investors to recognize that, in the face of financial downturns such as the COVID-19 pandemic, screened stock markets may not offer a practical means to hedge against traditional indices.

6.3. Policy Implications

The research has important implications for policy and government decision-making regarding the interplay between COVID-19 and financial markets. The findings suggest that governments should exercise additional caution when implementing preventive measures for COVID-19 to prevent potential future adverse impacts on the stock market. Understanding the limitations of Sharia-compliant indices as hedging tools during crises is crucial for developing robust financial policies. Policymakers should consider these insights to enhance risk management strategies and ensure market stability during future global disruptions.

In conclusion, our research provides valuable insights into the complex relationship between the COVID-19 pandemic and financial markets, particularly regarding conventional and Islamic indices. By highlighting enduring correlations, contagion effects, and the limitations of screened stocks during crises, this study contributes to the broader understanding of crisis resilience in financial markets and informs adaptive policymaking for future global challenges.

Author’s Contribution:

Zamrud Khursheed: Conceptualization, Validation, Formal analysis, Investigation, Methodology, Software, Resources, Data curation, writing – original draft, Writing – review & editing.

Moghis Ur Rehman: Review & Editing, Validation, Project administration, Supervision, Final Approval.

Moeez Ahmad: Writing & editing, Resources, Funding acquisition.

Ahmad Ali: Review & Editing, Funding acquisition.

Conflict of interest/ Disclosures:
The authors declared no potential conflicts of interest w.r.t the research, authorship and/or publication of this article.

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