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EMPIRICAL EVALUATION OF STOCK MARKETS COINTEGRATION IN THE AFTERMATH OF COVID-19 AND INVESTMENT IMPLICATIONS

Nnamdi Obiosa, PhD
School of Accounting and Finance
Bloomsbury Institute London, United Kingdom
ORCID identifier: 0000-0002-6375-3857
nnamdi.obiosa@bil.ac.uk

Ashiq Zaman, PhD
School of Accounting and Finance
Bloomsbury Institute London, United Kingdom
ORCID identifier: 0009-0004-0523-9544
ashiq.zaman@bil.ac.uk

Abstract

This paper evaluates the stock market cointegration as a result of COVID-19 and the investment implications, among six countries representing four major continents. We use the Gregory and Hansen cointegration test, to avoid any structural change issue within the time series, to test if one stock market cointegrates with another and the multivariate Dynamic Conditional Correlation model to estimate time-varying conditional correlation relationships among these stock markets. Using daily stock market data between January 2011 and December 2022 which we further divided into three sub-samples of pre, during and post COVID-19, the Gregory and Hansen results show a long-run relationship among sixty percent of the stock markets investigated before COVID-19. However, we find that there are no stable long-run relationships among eighty percent of the same stock markets after COVID-19, indicating potential portfolio diversification benefits for investors. Our findings using the Dynamic Conditional Correlation model show that stock market correlations are low before and after COVID-19 but find a *dramatic increase in correlation during the COVID-19 period and that the correlation starts to decrease after the crisis. Therefore, active investors should understand how markets cointegrate at normal times, during economic crises and after such crises as well as how they correlate and apply such in the design of investment portfolios to fully leverage on the inherent benefit of international diversifications.*

Keywords: Stock Market; Cointegration; COVID-19; Gregory and Hansen Cointegration Test; Dynamic Conditional Correlation

INTRODUCTION

A stock market is a marketplace where individuals and organizations can buy and or sell primary and secondary shares of public companies. The trading on the shares of these companies takes place through several stock exchanges operating all over the world. When an investor buys shares of a company in a stock exchange, the investor secures a claim on all potential benefits that are assigned from the company to the investor. The stock market can, therefore, be seen as an organized market system where their operations are conducted through the collective dealings of buyers and sellers. The existence of stock markets give assurances to investors in shares that should they want to liquidate their shareholdings they can easily do so, and this marketability of shares make them attractive to investors who constantly monitor the prices of shares in the market.

There are many stock markets scattered all over the world where the companies' shares are traded and their reaction to economic shocks are important to the investing public as well as to the companies whose shares are being traded. The price of share in the trading platform in the stock exchanges are normally set by the forces of demand and supply but this may be negated when global crises occur such as COVID-19. The COVID-19, being a pandemic was a global outbreak of infectious disease leading to hospitalizations and high death rates all over the world with resultant significant disruption to economic, social, and political order (Qiu et al. 2020; David et al. 2021).

It will be recalled that in December 2019, Wuhan Municipal Health Commission, China, after due diligence, reported for the first time the existence of coronavirus otherwise known as COVID-19. This spread sporadically in the first quarter of 2020 leading to lockdowns within countries and closure of countries borders and this drastically affected economic activities. The slowdown in economic activities had negative consequences as it affected the operations of businesses globally (Barro *et a*l. 2020; Costa *et a*l. 2022; Lee et al. 2022; Alabbad & Schertler 2022: Zenzius et. al. 2022). However, towards the end of the first quarter of 2021, the COVID-

19 restrictions started easing and by the end of the third quarter of 2021, most restrictions were removed in most countries leading to full economic activities.

The financial markets all over the world were directly impacted by COVID-19 as returns on the markets plummeted. The question, therefore, is whether all the stock markets react and move in the same way and level during such economic shocks. There has been increasing concern among financial economists and fund managers about changing asset price movements across various stock markets, as increasing cointegration reduces an investor's ability to portfolio diversification. Stock markets are strongly correlated with each other during a period of global economic uncertainty due to the interconnected design of the global financial system.

Global stock market correlations are mainly used to discover the profitability or otherwise from international risk diversification (Narayan 2019), and it has been observed that there is a high correlation among equity returns in the bear markets and a low correlation in the bull markets. Generally, an investor can achieve portfolio diversification by investing in various stock markets with low or negative correlations. This can only be possible if there is an understanding of how the stock markets cointegrate during economic shocks such as the impact of COVID-19 and thereafter. Morse et al. (2012) alluded to the fact that the human race is susceptible to health threats with substantial economic consequences. Therefore, investors need to understand integration among stock markets in the event of economic shocks if they are to leverage on diversification benefits hence the importance of this paper. Moreso, this is imperative since correlation among various stock markets can change abruptly due to these kinds of pandemic spreads. Therefore, this paper explores whether there is stock market cointegration and correlation in the aftermath of the COVID-19 crisis and in doing that, we divided the sample into three sub-samples: before, during, and after COVID-19 epidemics to gain this understanding which will be very useful to both the investing public and companies whose shares are being traded. Understanding the investment implications on stock market cointegration and correlation and applying this kind of knowledge in financial portfolio design will be very useful to investment professionals.

LITERATURE REVIEW

Prior to the COVID-19 pandemic, researchers have looked at the issue of cointegration of financial markets after crises which affected the global economy. Younis et.al. (2020) investigated stock market comovements among Asian emerging economies during the crisis's periods of 1997, 2008 and 2015 respectively. They found co-movement relationships of higher occurrences during the crisis's periods investigated. Their findings showed how dependent these economies are with each other during crises periods. Kenourgios and Samitas (2011) investigated the impact of the 2007–2009 financial crisis on developed European and Balkan markets using the dynamic cointegration method. They found that a time-varying correlation increased during the crisis. Furthermore, Gupta and Guidi (2012) found that the time-varying correlation between the Indian stock market and three developed stock markets rose dramatically during the crisis and returned to the initial level after the crisis. Ratanapakorn and Sharma (2002) investigated the interrelatedness between regional stock indices in relation to the 1997 Asian crisis namely among stock indices of the US, Europe, Asia, Latin America, and Eastern Europe–Middle East for the period before Asian crisis and during the crisis period. They found no long-run relationship before the Asian financial crisis among the stock indices sampled though they observed one main cointegrating vector which is short-term during the crisis. Jang and Sul (2002) investigated the change of cointegration among leading Asian markets. They attempted to find the impact of the 1997 Asian financial crisis but did not give evidence of cointegration before the financial crisis.

In December 2019 came the COVID-19 pandemic, which spread across the globe like wildfire leading to health challenges, deaths, and serious economic disruptions. As expected, many researchers have published papers in relation to COVID-19 and its impact on various economic activities. Some of these articles focused on a certain country or group of countries (Faque & Hacioglu 2021; Das & Gupta 2022; Salman & Ali 2022; Xu & Lien 2022; Zhang et.al. 2022), while others focused on a particular product (Mensi et.al. 2020; Yarovaya et.al. 2021; Apergis et.al. 2022; Zenzius et. al. 2022) or sectoral economies (Hassan et.al. 2021; Rakshit & Neog 2022). Since the world economy is becoming more and more integrated and interdependent, questions are being raised about the cointegration of the financial markets as curious investors want to know whether there is co-movement within the markets and how best to leverage on diversification benefits. This is more expedient to understand, especially during crises that have an impact on the economy, such as COVID-19. Our focus on this research is whether there is cointegration within the stock markets because of COVID-19 and what values investors and policy makers can derive from such knowledge. Financial economists and researchers have looked at the impact of the COVID pandemics on the stock market from different angles.

Faque and Hacioglu (2021) examined the effect of the COVID-19 pandemic on stock markets, gathering facts from global equity indices. The study collected data from 12 representative global equity indices, and their study, among other findings indicated that there is co-movement in global equity indices which is quite insightful. However, collecting all but one data in U.S. dollars may have some implication on their findings due the different exchange rate regimes among the countries. Again, there is no direct test of the relationship among the different equity markets. Similarly, Das and Gupta (2022) carried a study on the cointegration of stock markets after the first COVID wave and looked at the relationships among the five most affected countries then. The results were a mixed one as they concluded that there was no cointegration among three of the sampled countries with cointegration only among the other two. They alluded to the fact that this was a result of the countries not sharing the same economic or political association, however, this could also be in part due to the short time frame of 3 months employed in their studies. It should be noted that in a study carried out by Salman and Ali (2021) on the effect of COVID-19 on countries in Gulf Cooperation Council (GCC) stock markets, revealed a negative short-term effect and being less impacted by the pandemics in comparison to the world stock markets.

Another study of interest is the cointegration of U.S. and Chinese stock market in relation to COVID-19 by Song et.al. (2022) which showed that both markets are integrated as there is co-movement and as such does not offer diversification benefits to investors in periods of economic downturn such as COVID-19. Of note is the fact that they divided their study into two parts by looking at the data set of pre-COVID-19 and that of during COVID-19, which is fascinating, however, the timeline for the split of the data was not documented. Zhang et. al. (2022) looked at the effect of COVID-19 shudders on the volatility of stock markets in five technologically advanced countries namely China, Switzerland, Sweden, Netherlands, and UK. The research was primarily to understand the impact of returns volatility occasioned by COVID-19 coming to China stock market from the advanced countries sampled and vice visa. Their study found that while there is no evidence of significance of return volatility emanating from these advance countries to China there is, however, a significant effect of China stock market in the explanation of these advance countries market volatility except that of USA. This information is beneficial to investors in their investment decisions.

Over the past few years, information technology has developed enormously. Advanced information technology causes information flows between international financial centres instantly. Due to the rise of capital movement from one financial centre to another and the movement of information, research on capital market integration has increased in empirical finance. A financial crisis usually leads to high financial market volatility, as financial markets become unsettled. This causes strong price movements in financial markets across the globe. Bhowmik et.al. (2022), in their research in relation to how emergent stock markets react during crisis periods including COVID-19 and how financial connections increase volatility spill-over effects, mentioned that volatility and return spill overs perform in reverse as time progresses and that market boundary is feeble, however, in times of crises they become sturdy.

The literature reviewed also showed difference in methodological approached adopted to investigate cointegration. The most dominant approach used is the Johansen test which was applied in several studies such as that by Das and Gupta (2022), Song et.al. (2022), Faque and Hacioglu (2021) David et al. (2021). However, the Johansen model applied by these researchers do not consider structural break in the time series and the strength of cointegration test is reduced significantly when there is a structural break in the time series.

Some literature suggests that international correlations among equity markets are not constant over time (Goetzmann et al., 2003). Several studies indicate that dynamic conditional correlation can change its path due to common external shocks like financial crises (Liu et al. 1998; Chiang & Chen 2016) and COVID-19 (Faque & Hacioglu 2021). Motivated by the issue of how external shocks can change the stock market cointegration, this research examines the stock market cointegration in the aftermath of COVID-19 specifically.

Having carefully reviewed available literature we discovered a gap which this research study attempts to fill. Our study is the only study that collectively has the following characteristics.

- Covered stock markets in six countries namely United Kingdom (UK), United States of America (USA), Germany, India, China, and South Africa representing four major continents of the world.
- Our sample data covered pre-COVID, during COVID and post-COVID periods in order to fully understand whether the stock markets cointegrates.
- Our methodological approach includes the application of descriptive statistics and correlation matrix, Gregory Hansen Cointegration Test after duly testing the data for being non-stationary; and Dynamic Conditional Correlation (DCC) - Generalized AutoRegressive Conditional Heteroskedasticity (GARCH).

The hypotheses developed in the methodology section were based on the foundation we laid for this research in our introduction section, and the literature reviewed and analyzed above. We are confident that the result of this study will be beneficial to investors, traders, financial economist, and the academic community.

METHODOLOGY

To determine if the stock markets are correlated and if one stock market is cointegrated with another and to assess the time-varying correlation between stock markets, we utilize various methodologies and econometric models we believe will best suit our research effort.

This paper's primary focus is the evaluation of stock market cointegration because of COVID-19. In undertaking this research, we acknowledge and assume as a universal truth that the stock market is efficient, therefore, the share price is always true since it articulates all the expectations of return and risk as perceived by investors. We recognize the existence of risk factor, especially risk factor associated with expectations of future government policies and economic conditions but does not want to deviate from the focus of our research as the investor is expected to hold a diversified portfolio and any systematic risk will be reflected in the share price which will be a function of the stock market. Therefore, we have concentrated on economic factors as explanatory variable.

We employ the following econometric models, descriptive statistics to assess the financial data distribution and correlation matrix to evaluate the linear correlation between stock returns. We also use Gregory Hansen Cointegration Test after duly testing the data for being non-stationary to scrutinize for cointegration among selected stock markets; and Dynamic Conditional Correlation (DCC) to assess the time-varying correlation between stock markets, as discussed in the following sub-headings.

Descriptive statistics and correlation matrix

Following Zhang et al. (2021), we use descriptive statistics to represent the basic feature of financial data. The descriptive statistics show Skewness, Kurtosis, the Jarque-Bera test and probability. The skewness value shows the skewness of return distribution, and the Kurtosis value shows the heaviness of tails distribution. Jarque-Bera test allows us to test the null hypothesis of normal distribution.

Furthermore, we also use a correlation matrix to evaluate the relationship between two variables: two stock market returns. We utilize the Pearson correlation to measure the relationship's strengths between the two stock markets. The correlation coefficient varies between +1 and -1, where positive 1 indicates a strong positive correlation and negative 1 shows a strong negative correlation (Isogai 2016). A correlation of 0 indicates no relationship at all.

Unit Root Test

The Unit Root Test is the preliminary test for non-stationarity of the data that must be carried out before subjecting the data to the Gregory Hansen Cointegration Test. Most financial time series data have non-stationary behaviour (Engle and Granger 2003). When two-time series data are non-stationary, the regression between these two time-series data may give a high R-Squared even if these time-series data are entirely unrelated. The regression between the unrelated time series is called spurious regression (Granger and Newbold 1974). So, checking whether each financial time-series are stationary or contain a unit root (non-stationary) is required before regression between two financial time series data is undertaken. There is a range of unit root tests available in econometrics. Each of these tests has some advantages and some disadvantages. This research uses both the Augmented Dickey-Fuller (ADF) and Zivot-Andrews Unit root tests to overcome the weaknesses of each test.

Augmented Dickey-Fuller (ADF)

We employ Augmented Dickey-Fuller (ADF) test suggested by Dickey and Fuller in 1979. The ADF test uses the Autoregressive (A.R.) model to investigate the existence of unit root. One of the most used A.R. models is $y_t = \beta + \rho y_{t-1} + \varepsilon_t$ where y_t represents the variable of interest, t means the time index, ρ represents the coefficient, and ε defines disturbance terms. In this study, the Augmented Dickey-Fuller (ADF) test is run based on the following regressions:

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

$$\Delta Y_t = \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon \quad (2)$$

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

Where, Δ represents the first difference operator, m represents the number of lags, ε_t represents pure white noise error term, and Yt represents time series. Equation (1) represents the pure random walk model without a constant and trend; and Equation (2) represents a random walk with a constant but without a time trend; and Equation (3) represents a random walk with a constant and time trend. Before doing the ADF test, it assumes that the error terms of the model are statistically significant, and it has a constant variance. This assumption of the ADF test is strict.

This study uses the following hypothesis for the Augmented Dicky Fuller (1979) test.

Null Hypothesis (H_0): Unit Root (i.e.: δ=0 means ρ=1 indicating the time series is non-stationary or it has a stochastic trend).

Alternative Hypothesis (H_1): No Unit Root (i.e., δ<0 indicating the time series is stationary or possibly around a deterministic trend)

Zivot-Andrews Test

We use the Zivot-Andrews (1992) Unit Root test over conventional unit root tests like Dickey-Fuller Generalised Least Squares (DF-GLS) and Phillips-Perron (P.P.) to check the non-stationary time series behaviour. The Zivot-Andrews test has the advantage of considering a structural break within the time series, whereas other traditional Unit root tests do not consider a structural break. Just like ADF test, the Zivot-Andrew's test runs with three different models to test the unit root. Equation (4) is model (A), and Equation (5) is model (B), allowing a change in the intercept and the slope accordingly. Equation (6) is model (C), which provides for a change in both intercept and slope (Ling et al. 2013).

$$\Delta y_t = \mathrm{m} + \alpha y_{t-1} + \beta_t + \mathrm{q} DU_t + \sum_{j=1}^{k} c_j \Delta y_{t-j} + \varepsilon_t \quad (4)$$

$$\Delta y_t = \mathrm{m} + \alpha y_{t-1} + \beta_t + \mathrm{g} DT_t^{*} + \sum_{j=1}^{k} c_j \Delta y_{t-j} + \varepsilon_t \quad (5)$$

$$\Delta y_t = \mathrm{m} + \alpha y_{t-1} + \beta_t + \theta DU_t + \gamma DT_t^{*} + \sum_{j=1}^{k} c_j \Delta y_{t-j} + \varepsilon_t \quad (6)$$

Where, DU_t Represents an indicator dummy variable for each possible break-date. DU_t = 1 if t> $T_{.B.}$ and zero otherwise. Where $T_{.B.}$ is time break. Furthermore, DT_t^{*} represent slop dummy. DT_t^{*}=t- $T_{.B.}$ if t> $T_{.B.}$ and zero otherwise (Ling et al. 2013). The Zivot-Andrews (1992) tests the null hypothesis of unit root against the alternative hypothesis of time series data are stationary.

Gregory Hansen Cointegration Test

The cointegration methodology developed by Engle and Granger (1987) and Johansen (1988) is used in many studies to investigate the relationship between international stock markets. These studies do not consider a structural break in the time series. According to Gregory, Nason and Watt (1996), the power of Engle and Granger's (1987) cointegration test is reduced dramatically when there is a structural break in the time series. To overcome these drawbacks of Engle and Granger (1987) and Johansen (1988), Gregory and Hansen (1996) proposed a new test which allowed one unknown structural break within the financial time series.

According to Gregory and Hansen (1996), cointegration between two financial time series may hold for a long time, and then it can move to a new long-run relationship. So, the time series are cointegrated in the sense that a linear combination of non-stationary variables is stationary. However, the linear combination has shifted at the unknown breakpoint. Considering this situation, Gregory and Hansen (1996), tested the null hypothesis of no cointegration against the alternative hypothesis of cointegration allowing one break. They suggested three alternative models which accommodate the changes in parameters of the cointegration vectors. These parameters are the level shift model or (C model, equation 7), level with a trend (or C/T model, equation 8) and changes in the intercept and slope model of the cointegration vector (or C/S, equation 9).

$$y\mathrm{t} = \mu 0 + \mu 1 \varphi \tau + \alpha \chi \mathrm{t} + \omega \mathrm{t} \quad (7)$$

$$\mathrm{yt} = \mu 0 + \mu 1 \varphi \tau + \beta \mathrm{t} + \alpha \chi \mathrm{t} + \omega \mathrm{t} \quad (8)$$

$$\mathrm{yt} = \mu 0 + \mu 1 \varphi \tau + \alpha 1 \chi \mathrm{t} + \omega \mathrm{t} \quad (9)$$

The dummy variable φt, which captures the structural change, is presented as follows:

$$\Phi_t = \begin{cases} 1 & if\ t > \tau \\ 0 & if\ t \le \tau \end{cases}$$

Where, τ∈ (0,1) is the relative timing of the change point, equations (7-9) are estimated sequentially with the breakpoint changing. The statistics which are calculated in the cointegration tests are ADF test statistics, Phillips Z_a and Phillips Z_t statistics. We use these three statistics to test the null hypothesis of no cointegration.

This study uses the following hypothesis for Gregory Hansen's (1996) cointegration test:

Null Hypothesis (H_0): One stock market (such as S&P 500) is not cointegrated with another stock market (such as FTSE100)

Alternative Hypothesis (H_1): One stock market (such as S&P 500) is cointegrated with another stock market (such as FTSE100)

These hypotheses were developed based on the foundation we laid for this research in our introduction, and literature reviewed and analyzed in the earlier sections.

Dynamic Conditional Correlation (DCC)

The importance of understanding co-movements of stock markets has been acknowledged in the literature review. Some studies have shown that stock market correlation tends to increase during a period of great market uncertainty (Virk and Javed 2017). One of our objectives for this study is to understand the impact of COVID-19 on stock market correlation. To capture the effect of COVID-19 on stock market correlation, we used the DCC-GARCH model proposed by Engle (2002).

Because our objective is to consider the dynamic nature of the co-movement of stock returns, we propose the use of the DCC-GARCH model. The DCC-GARCH model allows the conditional volatility and correlations to vary over time, which accounts for the stock market's dynamic behaviour. It should be noted that studies that want to investigate the presence of asymmetric effect of shocks could use an asymmetric version of the Dynamic Conditional Correlation model of Engle (2002). Since widespread evidence have been found that national equity index return series show strong asymmetries in conditional volatility (Cappiello et. al. 2006; Rao et. al. 2022; Al-Nassar & Makram 2022), we have excluded that aspect in our research.

We employ the multivariate DCC model Engle (2002) introduced to assess the time-varying correlation between stock markets which is a variant of Generalized AutoRegressive Conditional Heteroskedasticity (GARCH). The multivariate DCC model allows the researcher to infer cross-market conditional correlations directly. First, it has assumed that stock market returns from the k series are multivariate and normally distributed. The k series of stock market returns have zero mean and conditional variance matrix H_t. We use the following multivariate:

$r_t = \mu_t + \varepsilon_t, \varepsilon_t \vdots I_{t-1} \longrightarrow N(0, H)$ (10)

Where, r_t represents (k×1) vector of stock returns.

$H_t \equiv D_t R_t D_t$ (11)

Where, D_t represents $(k \times k)$ matrix of time-varying standard deviations of the return on each market in the sample, Rt represents $(k \times k)$ conditional correlation matrix.

$$\mu_{i,t} = \delta_{i0} + \delta_{i1} r_{i,t-1}$$

The D_t and R_t can be represented as follows:

$D_t = \text{diag}\left(h_{11t}^{\frac{1}{2}} \ldots \ldots h_{kkt}^{\frac{1}{2}}\right)$ (12)

in Equation (12) $hiit$ represents univariate GARCH (1,1) process.

$R_t = (\text{diag}Q_t)^{-\frac{1}{2}} Q_t (\text{diag}Q_t)^{-\frac{1}{2}}$ (13)

in Equation (13) $Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha\mu_{t-1}\mu'_{t-1} + \beta Q_{t-1}$ which refers (k×k) symmetric positive definite matrix.

The conditional correlation coefficient can be represented as ρ_{ij}. Where ρ_{ij} is conditional correlation coefficient between stock market i and j. ρ_{ij} can be written as follows:

$\rho_{ij} = \frac{(1-\alpha-\beta)\overline{q_{ij}}+\alpha u_{i,t-1}u_{j,t-1}+\beta q_{ij,t-1}}{((1-\alpha-\beta)\overline{q_{ij}}+\alpha u_{i,t-1}^2+\beta q_{ii,t-1})^{1/2}((1-\alpha-\beta)\overline{q}_{ij}+\alpha u_{j,t-1}^2+\beta q_{ij,t-1})^{1/2}}$ (14)

The log-likelihood of the observation on ε_t is given by equation (14). From equation (14), specially ρ_{ij} measures the direction and strengths of correlation between two stock returns. If the ρ_{ij} is positive, the correlation between these two stock markets moving in the same direction. However,if ρ_{ij} is negative, then the stock market moves in the opposite direction. The parameters of equation (14) are estimated using the quasi-maximum likelihood method (QML).

$L = -1/2 \sum_{t=1}^{T}(n\log(2\pi) + \log|D_t R_t D_t| + \varepsilon'_t D_t^{-1} R_t^{-1} D_t^{-1} \varepsilon_t)$ (15)

equation (15) can be written as follows by using $u_t = \frac{\varepsilon_t}{\sqrt{h_t}} = D_t^{-1}\varepsilon_t$

$L = -1/2 \sum_{t=1}^{T}(n\log(2\pi) + 2\log|D_t| + \log|R_t| + u'_t R_t^{-1} u_t)$ (16)

The parameter estimates of the DCC-GARCH model test the null hypothesis of time-varying volatility. The statistically significant estimates will indicate time-varying volatility. Furthermore, If the sum of estimated coefficients is close to unity, the pairwise correlation among stock markets will have high persistent behaviour (Gupta and Guidi, 2012).

Sampling and Data Collection

We use daily stock index prices of the UK (FTSE100), USA (S&P500), Germany (DAX30), India (S&P Sensex), China (Shanghai SE) and South Africa (FTSE/JSE) from 1st January 2011 to 31st December 2022. All indices were collected from Thomson Reuters DataStream in local currency to avoid bias from exchange rate changes.

It is documented in the financial literature that Stock market cointegration is affected by external shock. In this paper, our focus is on the evaluation of the impact of the most recent external shock, which is COVID-19. Before 2011, the global financial crisis and European debt crisis affected the stock markets, and we only wanted to evaluate the impact of COVID-19, so this paper took January 2011 as the starting point for the chosen data time series. In deciding the beginning and end of COVID-19 period, we followed the timeline of UK government coronavirus lockdowns and measures, March 2020 to December 2021, as released by Institute for Government 2022. To evaluate the impact of COVID-19, we have divided our sample period into three sub-samples. The dates corresponding to the three sub-samples for which the relevant market data were collected for analysis are as follows:

- Pre COVID-19 Period: 1st January 2011 to 31st December 2019
- COVID-19 Period: 1st January 2020 to 31st July 2021.
- Post COVID-19 Period: 1st August 2021 to 31st December 2022.

RESULTS AND DISCUSSION

Pattern of daily stock prices and volatility

Figures 1 and 2 represent the daily stock market indices and volatility patterns across all markets. Figure 1 shows that every stock market was affected by COVID-19 between January 2020 and July 2021. Furthermore, the figure suggests evidence of structural breaks as there are upward and downward movements. Similarly, Figure 2 shows increasing volatility across the selected stock markets during the COVID period. We can also see that China stock market has more significant fluctuations than other stock markets.

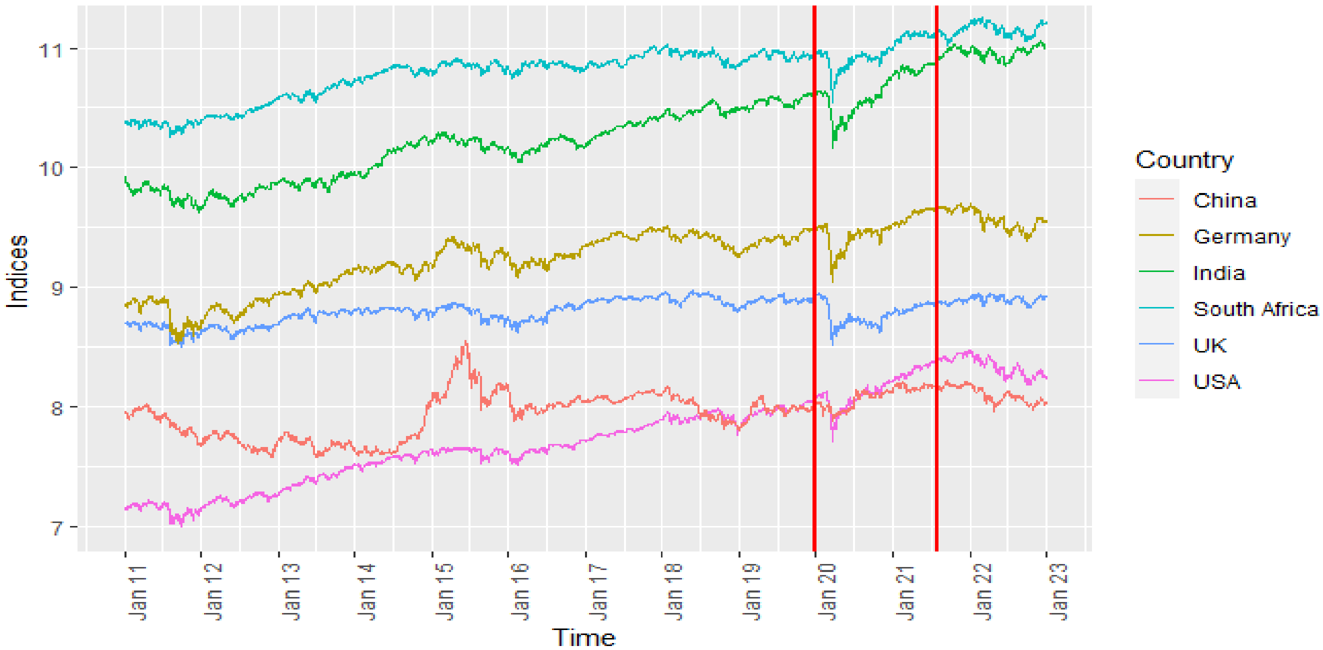


Figure 1: Pattern of daily Stock Indices of six stock markets between 1st Jan 2011 and 31st Dec 2022

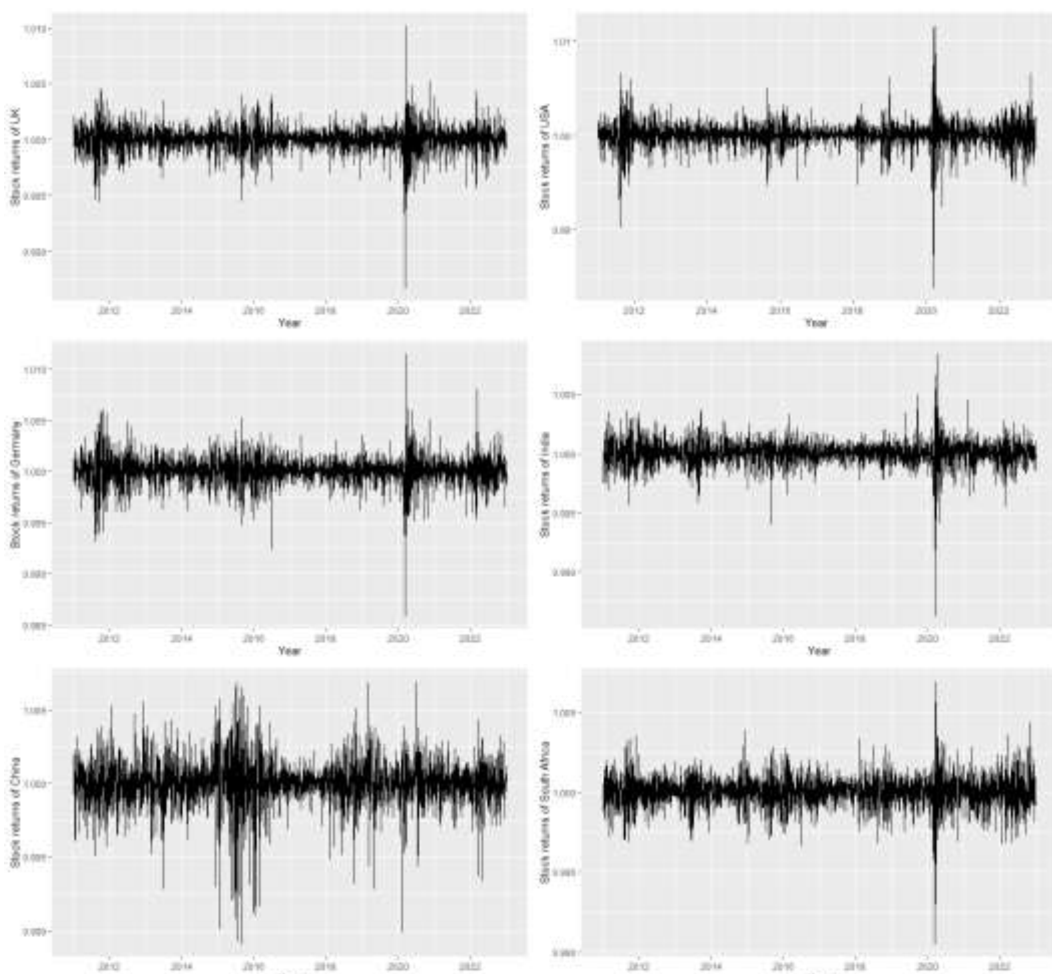


Figure 2: Pattern of daily Stock returns of six stock markets between 1st Jan 2011 and 31st Dec 2022

Results of Pearson correlation matrix

Tables 1, 2 and 3 present the Pearson correlation coefficient for the daily stock market returns. We calculate the stock return using the Continuously compounded stock returns formula below for each price index.

$R_t = [ln(P_t/P_{t-1})]$. -------------------- (17)

Were, R_t = Daily stock return for the chosen stock market; ln= natural log of daily stock prices. p_t = daily stock price at time t; p_{t-1} = daily stock price on the previous day.

We find all stock markets are positively correlated with each other. The results indicate that Germany and UK stock markets are highly correlated in all three sub-samples. On the other hand, China-USA has the weakest correlation. Looking at all three sub-samples, we can observe that the correlation among stock markets changes over time. The results also show that correlation increased between all stock markets during the COVID-19 period. For instance, we observe that the highest correlation between Germany and UK (about 0.82 or 82%) before COVID increased to 0.88 or 88% during the COVID but changed again after the COVID, to 0.81 or 81%.

It should be noted that the weakest correlations exist between China and all the other stock markets in all the sub-sample periods, and this represents a valuable investment diversification opportunity. Next in weakness is India to other stock markets evaluated and followed by South Africa to other stock markets. South Africa have a noticeable degree of correlation to the stock markets of developed economies of UK and Germany but a weaker correlation to the USA stock market. Evidence based on this analysis suggests that a portfolio value can be enhanced with equities from developed markets namely UK, Germany, USA alongside equities from China and India. For a typical European investor, while South Africa may not offer exceptional benefits like China or India, it will nonetheless offer better benefits to USA investors. It should be noted that equities from China offers the highest diversification benefits due to its low correlations across board with other markets.

Table 1: Pearson Correlation coefficient of daily stock market returns: (Pre COVID-19)

	UK	USA	Germany	India	China	South Africa
UK	1.00					
USA	0.58	1.00				
Germany	0.82	0.61	1.00			
India	0.37	0.24	0.37	1.00		
China	0.19	0.13	0.15	0.20	1.00	
South Africa	0.64	0.41	0.60	0.39	0.24	1.00

Table 2: Pearson Correlation coefficient of daily stock market returns: (COVID-19 Period)

	UK	USA	Germany	India	China	South Africa
UK	1.00					
USA	0.66	1.00				
Germany	0.88	0.66	1.00			
India	0.54	0.38	0.52	1.00		
China	0.27	0.23	0.25	0.36	1.00	
South Africa	0.76	0.59	0.76	0.61	0.39	1.00

Table 3: Pearson Correlation coefficient of daily stock market returns: (Post COVID-19)

	UK	USA	Germany	India	China	South Africa
UK	1.00					
USA	0.40	1.00				
Germany	0.81	0.52	1.00			
India	0.48	0.27	0.20	1.00		
China	0.18	0.01	0.12	0.21	1.00	
South Africa	0.63	0.35	0.57	0.41	0.36	1.00

Descriptive statistics

Table 4 below presents the summary statistics of the sample data for all three sub-samples. For the pre COVID-19 period, we observe that the stock market returns for all selected stock markets are not normally distributed as skewness value exceeds zero. The negative skewness for all the stock markets indicates that the data are skewed to the left, with a relatively longer left tail than the right one. The positive kurtosis value indicating the stock return distributions are more picked than usual. Furthermore, based on the Jarque-Bera test, we found that the stock returns do not follow the normal distribution for the pre COVID period as the P value is close to zero, less than the 5% significance level. So, the Jarqu-Bera test rejects the null hypothesis of data following a normal distribution. Likewise, Rachev et al. (2005) reject the normality assumption of stock return. We also find negative skewness for stock return during COVID-19 and post COVID-19. The kurtosis for all stock markets across the three sample periods is larger than three, indicating that all the stock return series are leptokurtic. So, these stock return series have fat tails and high peaks.

Table 4: Descriptive statistics of daily stock market returns

Panel A: pre-COVID	**UK**	**USA**	**GERMANY**	**INDIA**	**CHINA**	**South Africa**
Skewness	-0.239	-0.556	-0.305	-0.064	-0.905	-0.179
Kurtosis	5.861	9.052	6.263	5.502	9.743	4.481
Jarque-Bera	822.727	3703.809	1077.450	614.0344	4767.339	226.9241
Probability	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: COVID	UK	USA	GERMANY	INDIA	CHINA	South Africa
Skewness	-1.102	-0.964	-0.976	-1.725	-0.904	-1.152
Kurtosis	14.536	16.621	16.193	19.624	10.685	12.229
Jarque-Bera	2373.575	3256.855	3060.819	4960.868	1072.579	1557.197
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: Post-COVID	**UK**	**USA**	**GERMANY**	**INDIA**	**CHINA**	**South Africa**
Skewness	-0.462	-0.088	0.256	-0.438	-0.761	0.153
Kurtosis	6.054	4.085	6.749	4.749	6.777	4.186
Jarque-Bera	156.899	18.616	220.769	58.967	255.672	23.144
Probability	0.000	0.000	0.000	0.000	0.000	0.000

Results of Unit Root test

Engle and Granger (2003) state that most financial time series have non-stationary behaviour. The financial time series must be stationary and integrated in the same order to carry out the cointegration test. Tables 5, 6 and 7 describe the results of the Augmented Dickey-Fuller (ADF) test (Dickey &Fuller 1979) and the Zivot-Andrews (1992) test for unit root. The results show that all-time series data are not stationary at the log level, but all the series are stationary at the first difference and all the time series data are integrated at level one for all three sub-samples hence we proceed with the Gregory and Hansen Cointegration test.

Table 5: ADF and Zivot-Andrews test result (Pre COVID-19: January 2011 to December 2019)

	Augmented Dickey-Fuller (ADF)			Zivot-Andrews (ZA)		
	Intercept	Trend & Intercept	None	Intercept	Trend	Both
UK	-47.127	-47.117	-47.132	-4.818	-4.415	-4.834
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
USA	-50.306	-50.296	-50.212	-4.763	-4.296	-5.035
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Germany	-46.653	-46.643	-46.639	-4.014	-3.898	-4.061
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
India	-45.449	-45.458	-45.414	-4.877	-4.118	-4.898
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
China	-46.803	-46.796	-46.812	-4.783	-2.494	-4.588
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	-48.789	-48.787	-48.766	-4.459	-5.652	-5.652
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Critical Values			
1%	-3.433	-3.962	-2.566	-5.340	-4.930	-5.57
5%	-2.863	-3.412	-1.941	-4.800	-4.420	-5.08
10%	-2.567	-3.128	-1.617	-4.580	-4.110	-4.82

Table 6: ADF and Zivot-Andrews test result (COVID-19 Period: January 2020 to July 2021)

	Augmented Dickey-Fuller (ADF)			Zivot-Andrews (ZA)		
	Intercept	Trend & Intercept	None	Intercept	Trend	None
UK	-21.060	-21.134	-21.083	-5.874	-5.0767	-5.907
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
USA	-5.444	-5.5022	-5.389	-5.249	-4.325	-5.243
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Germany	-12.401	-12.416	-12.407	-4.784	-4.025	-4.778
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
India	-8.335	-8.414	-8.311	-4.360	-4.000	-4.365
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
China	-20.228	-20.204	-20.245	-4.868	-3.419	-4.716
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	-21.269	-21.285	-21.277	-4.228	-3.760	-4.218
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Critical Values						
1%	-3.433	-3.962	-2.566	-5.340	-4.930	-5.57
5%	-2.863	-3.412	-1.941	-4.800	-4.420	-5.08
10%	-2.567	-3.128	-1.617	-4.580	-4.110	-4.82

Table 7: ADF and Zivot-Andrews test result (After COVID-19: August 2021 to December 2022)

	Augmented Dickey-Fuller (ADF)			Zivot-Andrews (ZA)		
	Intercept	Trend & Intercept	None	Intercept	Trend	None
UK	-20.314	-20.286	-20.338	-4.436	-3.754	-4.523
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
USA	-19.071	-19.050	-19.081	-4.184	-3.318	-4.080
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Germany	-19.787	-19.766	-19.803	-4.248	-3.739	-3.929
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
India	-18.408	-18.385	-18.414	-3.903	-3.874	-4.276
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
China	-19.610	-19.589	-19.619	-3.909	-3.179	-3.839
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
South Africa	-14.957	-14.940	-14.974	-3.862	-3.045	-3.921
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Critical Values						
1%	-3.433	-3.962	-2.566	-5.340	-4.930	-5.57
5%	-2.863	-3.412	-1.941	-4.800	-4.420	-5.08
10%	-2.567	-3.128	-1.617	-4.580	-4.110	-4.82

Gregory and Hansen Cointegration test

Gregory and Hansen (1996) state that the power of the standard cointegration test can be significantly reduced due to structural break within the time series. We apply the Gregory and Hansen (1996) cointegration test to avoid any structural change issue within the time series. Tables 8, 9 and 10 present the Gregory and Hansen cointegration test results for all the models (Level, Trend and Regime). Table 8 summarises the pre COVID-19 period, table 9 summarises the COVID-19 period, and table 10 summarises the post COVID-19 period.

Pre COVID (table 8), we find that the null hypothesis of no cointegration is rejected under at least one model for all the pairwise relationships between the UK and other stock markets except UK-China. This can also be said of the pairwise relationships between USA and other stock markets except USA-China. Whereas for Germany, the null hypothesis of no cointegration is rejected under at least one model for all the pairwise relationship with other stock markets except for Germany-China, and Germany-South Africa. Furthermore, the null hypothesis for no cointegration is accepted for the pairwise relationships between India-South Africa, and China-South Africa. In total, 60% of the stock markets investigated cointegrates. The results indicate that even though these stock markets are from different continents, they have a long-run relationship and stay close to each other. From the Gregory and Hansen cointegration results, we may conclude that before COVID, there was a long-run relationship between the UK and other selected stock markets except China. Similarly, there was a long-run relationship between the USA and other chosen markets except China. We can also find the long-run relationship between Germany and India. At the same time, China only has a long-run relationship with India. We wish to point out that because markets cointegrates in the long run does not mean that international diversification should be jettisoned as the benefits of international diversification is still attainable with proper portfolio articulation. Portfolio diversification is one of the most vital and significant developments in contemporary finance, and practice over the years have proved its success and depending on the degree of market correlations, has enhanced portfolio value. What is apparent from the pre COVID-19 cointegration analysis is that a portfolio with equities from China provides an obvious hedge to all the other countries equities except that of India. This is also true of portfolios with equities from Germany and South Africa, as well as that of India and South Africa.

The number of pairwise cointegration decreased during the COVID-19 period (refer table 9). The null hypothesis of no cointegration is rejected for the following: UK-USA, UK-India, USA-Germany, USA-India, USA-South Africa, and China-South Africa. On the other hand, the null hypothesis of no cointegration is accepted for the following: UK-Germany, UK-China, UK-South Africa, USA-China, Germany-India, Germany-China, Germany-South Africa, India-China, and India-South Africa. This is quite an interesting find for the investment professionals, the number of pairwise relations with no cointegration increased from 6 to 9, these additional pairwise countries equities namely UK-Germany, UK-South Africa, and Germany South Africa, with hindsight, will be good to have in any portfolio selection as this will offer real diversification benefits since the equity prices of stocks in these markets do not cointegrate during such pandemic with the resultant economic crises.

Similarly, for the post-COVID period (table 10), we find only three pairwise cointegration (UK-USA, UK-South Africa, and USA-India). From the result we can see that 12 pairwise relationships (80%) do not cointegrate for at least 17 months after the COVID-19 (1st August 2021 to 31st December 2022), covered by our research. The investment professionals should be curious and understand these relationships in the choice of equities from various countries when creating a portfolio as this kind of threats to economic life will simply not go away forever. From the result of the findings active investors should, with this knowledge, invest in the equities from these countries that do not cointegrate after such shocks to economic activities as by doing so they will fully leverage on the benefits of international diversification most appropriately.

Overall, we can conclude that we find mixed results from the Gregory and Hansen cointegration results. Before COVID, we find a long run relationship between some stock markets such as UK-USA, UK-Germany, UK-India), and we were unable to establish any long-run relationship between some stock markets such as China-South Africa, India-South Africa, Germany-South Africa. Similarly, we find mixed results of a long-run relationship between stock markets during and after COVID. The Gregory and Hansen cointegration test also indicates a decrease in the number of pairwise cointegration over time. The investing public can use this information in the selection of equities for their investment portfolios with a view to enhancing and benefiting from international portfolio diversifications.

Tables 8, 9 and 10 present the Long run cointegration test - Gregory and Hansen (1996) cointegration test. Here, *denotes rejection of null hypothesis at 5% level. The critical values for Gregory-Hansen are taken from Gregory-Hansen (1996). Critical values for ADF and Z_t are -4.61 for level (C), -4.99 for trend (C/T) and -4.95 for regime (C/S). Critical values for Z_a are -40.48 for level (C), -47.96 for trend (C/T) and -47.04 for regime (C/S).

Table 8: Gregory and Hansen (1996) Cointegration test. (Pre-COVID)

Countries	Model	ADF	Z_t	Z_a	Result
UK-USA	Level (C)	-4.37	-4.36	-39.52	No Cointegration
	Trend (C/T)	-5.61*	-4.99*	-75.12*	Cointegration
	Regime (C/S)	-4.63	-4.55	-42.35	No Cointegration
UK-Germany	Level (C)	-4.70*	-4.80*	-42.40*	Cointegration
	Trend (C/T)	-5.20*	-5.30*	-51.15*	Cointegration
	Regime (C/S)	-5.41*	-5.58*	-56.89*	Cointegration
UK-India	Level (C)	-4.09	-4.64*	-42.72*	Cointegration
	Trend (C/T)	-4.02	-4.66	-42.90	No Cointegration
	Regime (C/S)	-4.45	-5.37*	-55.69*	Cointegration
UK-China	Level (C)	-3.72	-3.74	-27.64	No Cointegration
	Trend (C/T)	-4.64	-4.74	-43.30	No Cointegration
	Regime (C/S)	-3.73	-3.77	-27.64	No Cointegration
UK-South Africa	Level (C)	-4.67*	-4.63*	-42.21*	Cointegration
	Trend (C/T)	-4.95	-5.01	-52.09*	Cointegration
	Regime (C/S)	-4.68	-4.64	-42.42	No Cointegration
USA-Germany	Level (C)	-4.50	-3.92	-38.94	No Cointegration
	Trend (C/T)	-6.11*	-5.44	-79.41*	Cointegration
	Regime (C/S)	-4.42	-3.87	-38.19	No Cointegration
USA-India	Level (C)	-5.44*	-4.90*	-53.92*	Cointegration
	Trend (C/T)	-6.01*	-5.63*	-73.74*	Cointegration
	Regime (C/S)	-5.29*	5.48*	-58.72*	Cointegration
USA-China	Level (C)	-3.11	-3.20	-19.95	No Cointegration
	Trend (C/T)	-4.55	-4.85	-47.23	No Cointegration
	Regime (C/S)	-3.13	-3.30	-21.13	No Cointegration
USA-South Africa	Level (C)	-3.80	-3.31	-32.55	No Cointegration
	Trend (C/T)	-4.52	-4.51	-50.80*	Cointegration
	Regime (C/S)	-3.80	-3.45	-34.40	No Cointegration
Germany-India	Level (C)	-4.78*	-4.74*	-42.45*	Cointegration
	Trend (C/T)	-4.60	-4.57	-41.26	No Cointegration
	Regime (C/S)	-5.31*	-5.38*	-52.05*	Cointegration
Germany-China	Level (C)	-3.23	-3.30	-22.23	No Cointegration
	Trend (C/T)	-4.42	-4.49	-38.53	No Cointegration
	Regime (C/S)	-3.46	-3.65	-23.96	No Cointegration
Germany-South Africa	Level (C)	-4.22	-4.04	-33.75	No Cointegration
	Trend (C/T)	-4.43	-4.25	-37.63	No Cointegration
	Regime (C/S)	-4.20	-4.06	-33.56	No Cointegration
India-China	Level (C)	-2.85	-2.93	-17.22	No Cointegration
	Trend (C/T)	-5.80*	-6.12*	-58.38*	Cointegration
	Regime (C/S)	-2.86	-2.93	-17.21	No Cointegration
India-South Africa	Level (C)	-4.15	-4.17	-30.85	No Cointegration
	Trend (C/T)	-4.67	-4.90	-31.34	No Cointegration
	Regime (C/S)	-4.67	-4.56	-42.21	No Cointegration
China-South Africa	Level (C)	-4.07	-4.14	-30.91	No Cointegration
	Trend (C/T)	-4.61	-4.69	-41.62	No Cointegration
	Regime (C/S)	-3.94	-3.98	-29.16	No Cointegration

Notes: * denote rejection of null hypothesis at the 5% level.

Table 9: Gregory and Hansen (1996) Cointegration test. (During COVID)

Countries	Model	ADF	Z_t	Z_a	Result
UK-USA	Level (C)	-3.94	-3.68	-25.34	No Cointegration
	Trend (C/T)	-4.81	-4.98	-57.59*	Cointegration
	Regime (C/S)	-4.00	-3.81	-35.43	No Cointegration
UK-Germany	Level (C)	-4.04	-4.10	-28.61	No Cointegration
	Trend (C/T)	-4.19	-4.25	-31.47	No Cointegration
	Regime (C/S)	-4.19	-4.27	-32.89	No Cointegration
UK-India	Level (C)	-4.40	-4.50	-35.43	No Cointegration
	Trend (C/T)	-4.58	-4.71	-40.63	No Cointegration
	Regime (C/S)	-4.87	-5.19*	-47.20*	Cointegration
UK-China	Level (C)	-4.29	-4.42	-35.62	No Cointegration
	Trend (C/T)	-4.28	-4.39	-35.12	No Cointegration
	Regime (C/S)	-4.55	-4.44	-38.59	No Cointegration
UK-South Africa	Level (C)	-3.72	-3.84	-26.72	No Cointegration
	Trend (C/T)	-3.93	-4.00	-29.61	No Cointegration
	Regime (C/S)	-4.23	-4.30	-34.56	No Cointegration
USA-Germany	Level (C)	-4.71*	-4.80*	-56.98*	Cointegration
	Trend (C/T)	-5.74*	-6.83*	-98.38*	Cointegration
	Regime (C/S)	-4.97*	-5.32*	-66.58*	Cointegration
USA-India	Level (C)	-3.70	-3.78	-40.51*	Cointegration
	Trend (C/T)	-4.15	-4.35	-48.84*	Cointegration
	Regime (C/S)	-3.95	-4.23	-47.46*	Cointegration
USA-China	Level (C)	-3.54	-3.39	-28.27	No Cointegration
	Trend (C/T)	-3.74	-3.63	-31.19	No Cointegration
	Regime (C/S)	-3.55	-3.40	-28.18	No Cointegration
USA-South Africa	Level (C)	-3.45	-3.72	-39.16	No Cointegration
	Trend (C/T)	-3.90	-4.46	-51.58*	Cointegration
	Regime (C/S)	-3.45	-3.72	-39.17	No Cointegration
Germany-India	Level (C)	-3.55	-3.82	-28.14	No Cointegration
	Trend (C/T)	-4.21	-4.34	-35.44	No Cointegration
	Regime (C/S)	-4.17	-4.31	-34.59	No Cointegration
Germany-China	Level (C)	-3.53	-3.45	-25.13	No Cointegration
	Trend (C/T)	-4.04	-3.74	-27.61	No Cointegration
	Regime (C/S)	-3.77	-3.51	-26.58	No Cointegration
Germany-South Africa	Level (C)	-4.12	-4.05	-32.03	No Cointegration
	Trend (C/T)	-4.17	-4.11	-32.73	No Cointegration
	Regime (C/S)	-4.04	-3.96	-30.75	No Cointegration
India-China	Level (C)	-4.19	-4.31	-36.62	No Cointegration
	Trend (C/T)	-4.29	-4.34	-35.42	No Cointegration
	Regime (C/S)	-4.18	-4.28	-36.36	No Cointegration
India-South Africa	Level (C)	-3.67	-3.90	-26.67	No Cointegration
	Trend (C/T)	-3.89	-4.12	-31.59	No Cointegration
	Regime (C/S)	-3.87	-4.00	-31.46	No Cointegration
China-South Africa	Level (C)	-5.60*	-5.73*	-58.89*	Cointegration
	Trend (C/T)	-5.55*	-5.69*	-58.41*	Cointegration
	Regime (C/S)	-5.60*	-5.78*	-59.43*	Cointegration

Notes: * denote rejection of null hypothesis at the 5% level.

Table 10: Gregory and Hansen (1996) Cointegration test. (Post-COVID)

Countries	Model	ADF	Z_t	Z_a	Result
UK-USA	Level (C)	-4.53	-4.70	-45.55*	Cointegration
	Trend (C/T)	-4.12	-5.21*	-55.29*	Cointegration
	Regime (C/S)	-4.94	-4.87	-46.98	No Cointegration
UK-Germany	Level (C)	-4.48	-4.51	-37.90	No Cointegration
	Trend (C/T)	-4.73	-4.73	-42.23	No Cointegration
	Regime (C/S)	-4.37	-4.44	-36.41	No Cointegration
UK-India	Level (C)	-3.77	-3.62	-25.83	No Cointegration
	Trend (C/T)	-4.60	-4.38	-36.41	No Cointegration
	Regime (C/S)	-4.11	-3.95	-30.86	No Cointegration
UK-China	Level (C)	-3.95	-3.83	-28.93	No Cointegration
	Trend (C/T)	-4.69	-4.57	-40.78	No Cointegration
	Regime (C/S)	-4.53	-4.51	-38.58	No Cointegration
UK-South Africa	Level (C)	-4.01	-3.88	-35.24	No Cointegration
	Trend (C/T)	-4.96	-5.07*	-52.85*	Cointegration
	Regime (C/S)	-4.29	-4.22	-40.60	No Cointegration
USA-Germany	Level (C)	-4.08	-4.08	-32.12	No Cointegration
	Trend (C/T)	-4.07	-4.08	-32.13	No Cointegration
	Regime (C/S)	-4.05	-4.05	-31.79	No Cointegration
USA-India	Level (C)	-4.46	-4.18	-32.04	No Cointegration
	Trend (C/T)	-5.45*	-5.07*	-51.06*	Cointegration
	Regime (C/S)	-4.48	-4.26	-32.94	No Cointegration
USA-China	Level (C)	-4.40	-4.43	-36.28	No Cointegration
	Trend (C/T)	-4.58	-4.49	-38.55	No Cointegration
	Regime (C/S)	-4.41	-4.44	-36.28	No Cointegration
USA-South Africa	Level (C)	-4.08	-4.17	-31.90	No Cointegration
	Trend (C/T)	-4.46	-4.64	-44.26	No Cointegration
	Regime (C/S)	-4.15	-3.98	-31.31	No Cointegration
Germany-India	Level (C)	-3.80	-3.72	-22.38	No Cointegration
	Trend (C/T)	-2.93	-2.88	-18.87	No Cointegration
	Regime (C/S)	-3.81	-3.73	-24.58	No Cointegration
Germany-China	Level (C)	-3.57	-3.45	-23.23	No Cointegration
	Trend (C/T)	-3.75	-3.67	-26.26	No Cointegration
	Regime (C/S)	-3.56	-3.43	-23.28	No Cointegration
Germany-South Africa	Level (C)	-4.05	-3.84	-29.65	No Cointegration
	Trend (C/T)	-4.08	-3.72	-28.91	No Cointegration
	Regime (C/S)	-4.92	-4.70	-43.75	No Cointegration
India-China	Level (C)	-3.57	-3.69	-21.22	No Cointegration
	Trend (C/T)	-3.60	-3.77	-22.29	No Cointegration
	Regime (C/S)	-3.67	-3.76	-21.43	No Cointegration
India-South Africa	Level (C)	-2.97	-3.11	-15.16	No Cointegration
	Trend (C/T)	-4.18	-4.19	-26.70	No Cointegration
	Regime (C/S)	-3.18	-3.17	-16.60	No Cointegration
China-South Africa	Level (C)	-4.03	-4.09	-28.49	No Cointegration
	Trend (C/T)	-4.39	-4.17	-30.40	No Cointegration
	Regime (C/S)	-3.95	-3.98	-27.44	No Cointegration

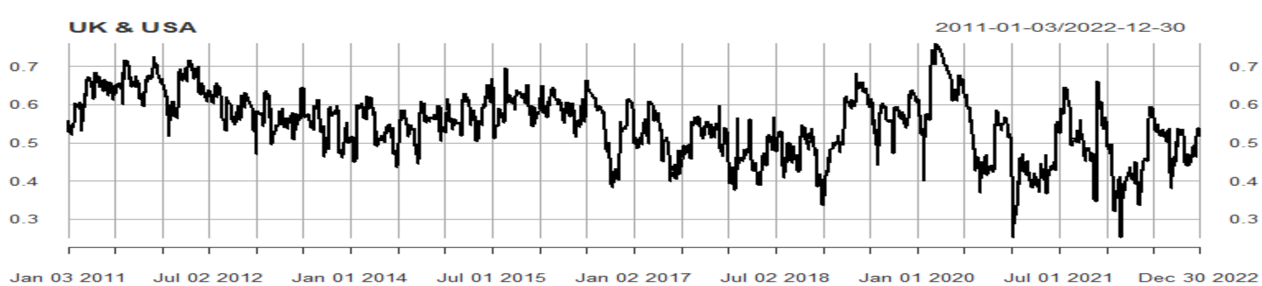
Notes: * denote rejection of null hypothesis at the 5% level.

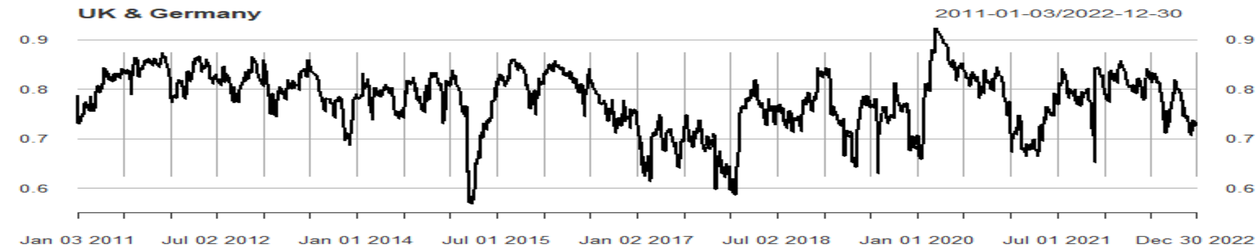
Results of Dynamic Conditional Correlation (DCC)

We recognize that the constant correlation coefficient could not show dynamic market conditions. Longin and Solnik (1995) state that the correlation among stock markets is unstable. We use the DCC-GARCH model Engle (2002) proposed to show the dynamic time-varying correlation among stock markets. The general correlation analysis, like Pearson correlation analysis, assumes that two variables are normally distributed (Isogai, 2016). Furthermore, the Pearson correlation is simply a coefficient from -1 to +1. It calculates a linear association between two-time series, which is different from the dynamic correlation, which shows the dynamic association between two-time series. However, in general, the financial return shows fat tail features. The multivariate DCC-GARCH model is more suitable for fat-tailed financial returns as the model can control volatility fluctuations to avoid any problem associated with spurious regression (Isogai, 2016).

Figure 3 shows the time-varying conditional correlation between all the selected stock markets. The highest correlation value was recorded between UK and Germany which was slightly above 0.9 in early 2020. Figure 3 also shows that the correlation between all the selected stock markets increased dramatically during the COVID lockdown in early 2020. Considering the UK and USA stock returns, the DCC model shows the highest correlation between the pair occurred during the COVID, over 0.7 in early 2020. We observe a similar pattern across all other relationships. This is as expected since it has been long established that markets seem to be most correlated when volatility is greatest as was the case during COVID-19. We can also observe a sharp decline in time-varying correlation after the COVID lockdown.

Our findings show that stock market correlations are low before and after global shocks like COVID-19. Our finding suggests that international investors can get diversification benefits before and after any shock. Our result is consistent with Gupta and Guidi (2012), who found a high correlation between stock markets during the COVID-19.




UK & Germany
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Jul 02 2018
Jan 01 2020
Jul 01 2021
Dec 30 2022


UK & India
2011-01-03/2022-12-30
0.50
0.45
0.40
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0.30
Jan 03 2011
Jul 02 2012
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UK & China
2011-01-03/2022-12-30
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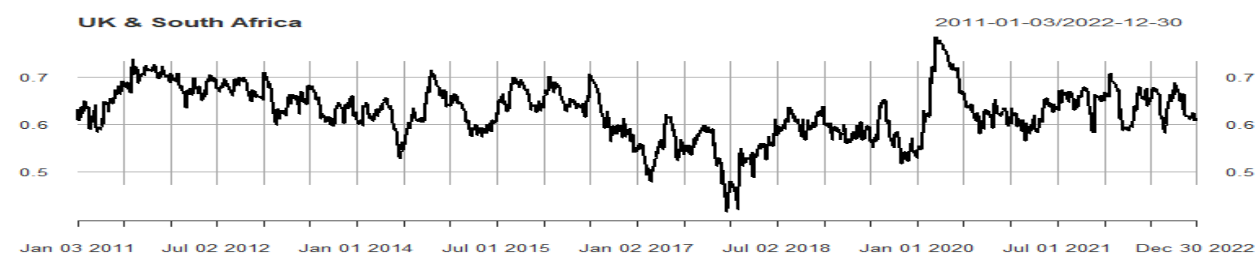
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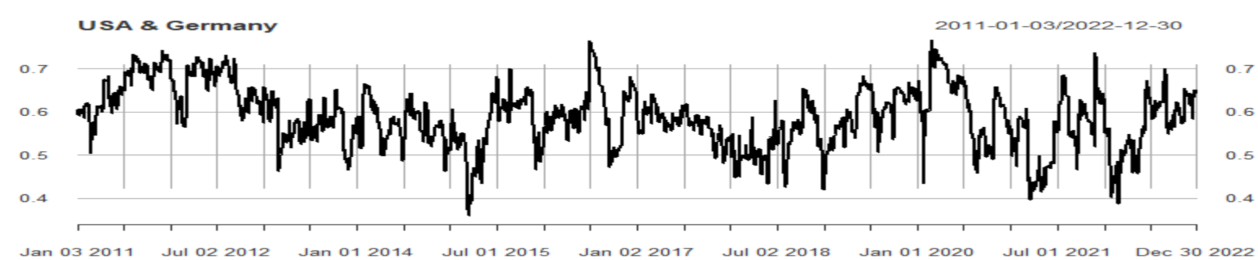
USA & Germany
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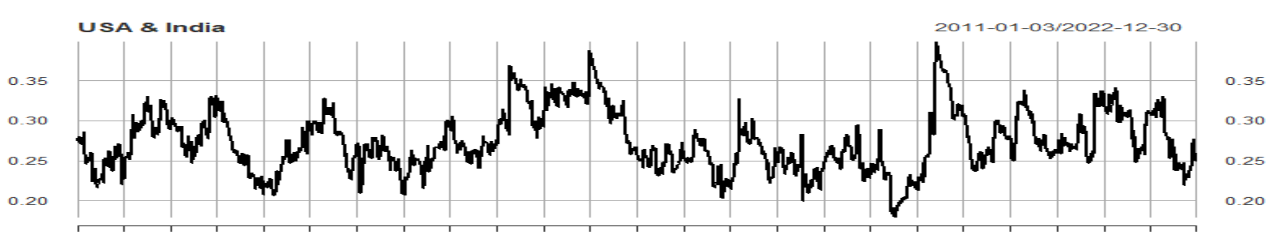
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USA & China
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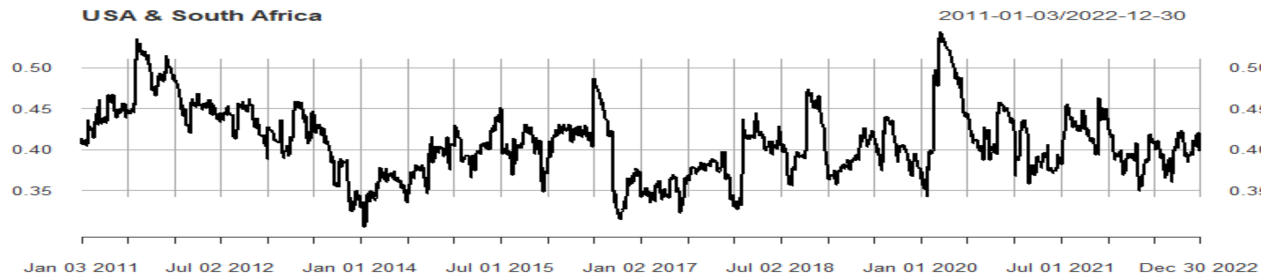
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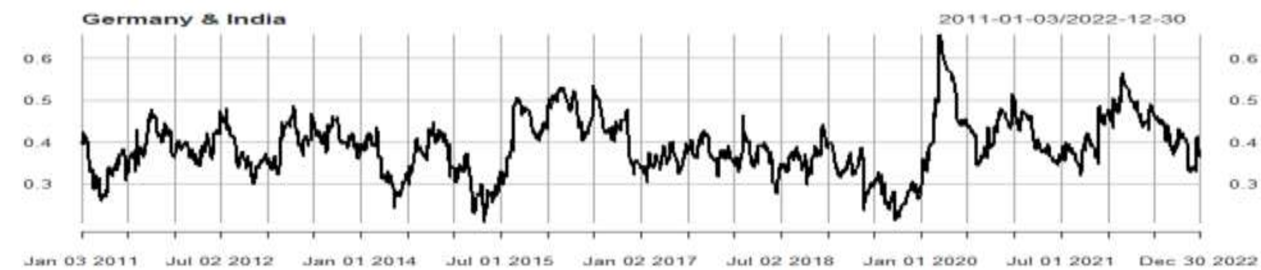
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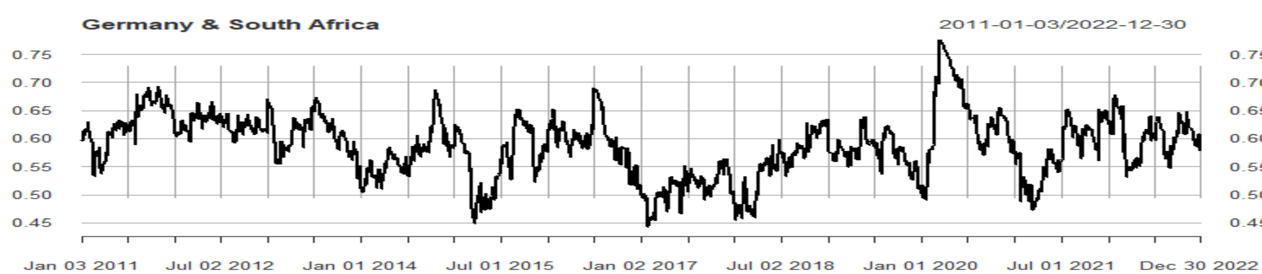
Germany & South Africa
2011-01-03/2022-12-30
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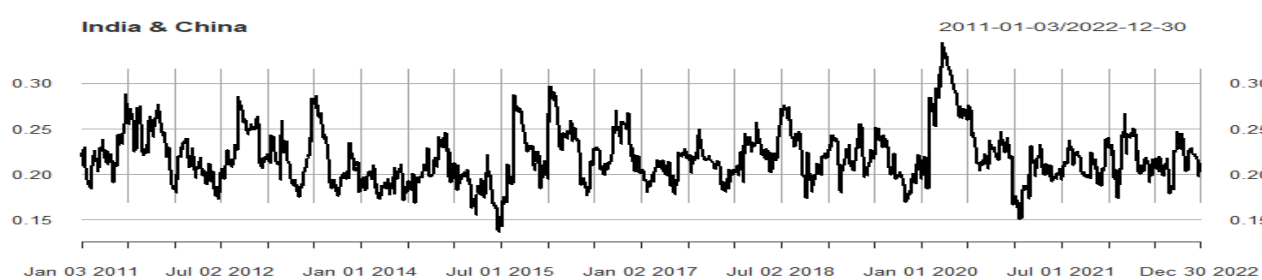
India & China
2011-01-03/2022-12-30
0.30
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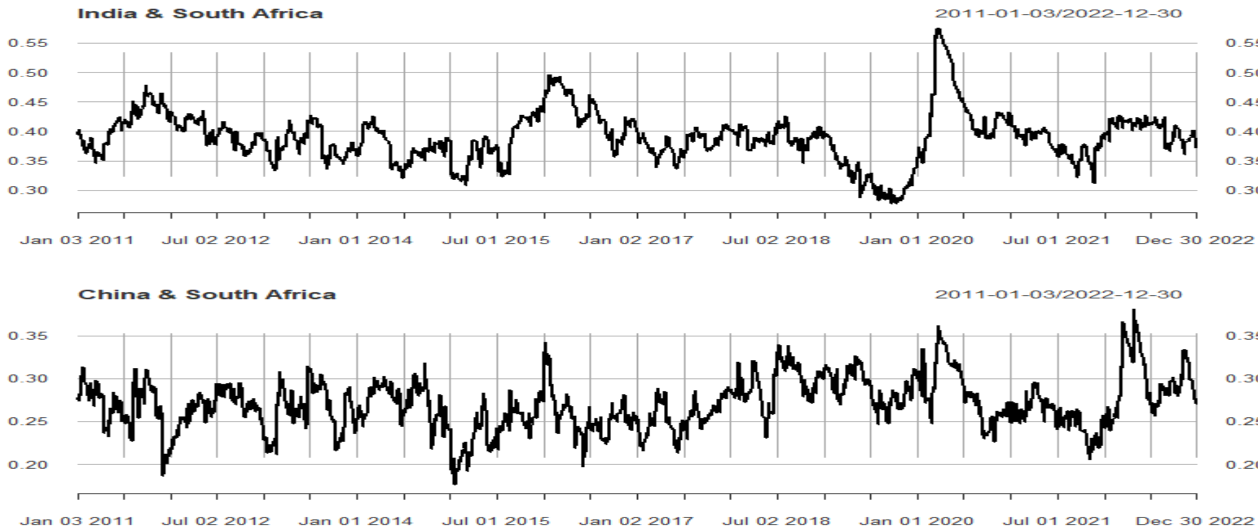

Figure 3: Time-varying correlations for pairwise stock market returns.

The DCC-GARCH analysis indicates that the short-term relationship between selected stock markets increased dramatically during COVID-19. However, the correlation decreased post COVID-19 period and returned to about the initial level. Like Gupta and Guidi (2012) and Chiang, Jeon and Li (2007), our study further confirms that correlation between the stock market increased during global shock. For instance, any natural disaster, financial crisis, or shock can create stock market volatility in a country that can be transmitted into another country and create volatility in that country's stock market. Eventually, this scenario will lead to an increase in correlation between these two countries stock markets.

It is imperative that the investment professionals understand these empirical discoveries and note that to be able to benefit from international diversifications, they may have to hold their portfolio positions and not go into panic selling or buying of equities unless they believe that the economic policy makers in a particular country will not respond appropriately to the economic shock that will lead to return to initial level in comparison to other countries. This is important since any market ability to return to the earlier level will depend on how quickly the economic policy makers adjust their policies in response to the shock.

Table 11: Results of the DCC-GARCH model:

Countries	DCC α-Probability	DCC β -Probability	DCC α-Estimate	DCC β-Estimate	(α+β) Estimate	Decision
UK-USA	0.012*	0.000*	0.011	0.982	0.992	Both short and long-run persistence
UK-Germany	0.000*	0.000*	0.037	0.940	0.977	Both short and long-run persistence

UK-India	0.001*	0.000*	0.013	0.967	0.980	Both short and long-run persistence
UK-China	0.999	0.000*	0.000	0.922	0.922	Only Long run persistence
UK-South Africa	0.045*	0.000*	0.012	0.979	0.991	Both short and long-run persistence
USA-Germany	0.357	0.000*	0.015	0.972	0.987	Only Long run persistence
USA-India	0.443	0.000*	0.001	0.993	0.994	Only Long run persistence
USA-China	0.753	0.000*	0.002	0.940	0.942	Only Long run persistence
USA-South Africa	0.535	0.000*	0.008	0.973	0.981	Only Long run persistence
Germany-India	0.009*	0.000*	0.009	0.978	0.987	Both short and long-run persistence
Germany-China	0.108	0.000*	0.004	0.991	0.995	Only Long run persistence
Germany-South Africa	0.000*	0.000*	0.018	0.965	0.983	Both short and long-run persistence
India-China	0.175	0.000*	0.009	0.919	0.928	Only Long run persistence
India-South Africa	0.004*	0.000*	0.012	0.971	0.983	Both short and long-run persistence
China-South Africa	0.652	0.000*	0.005	0.978	0.983	Only Long run persistence

Note: * indicates the significance level at 5%.

The constant correlation coefficient is not able to show the dynamic market conditions. However, the DCC-GARCH model can show dynamic market conditions, this is further analysed in table 11 above.

- The summation of α and β is less than one, which indicates the dynamic relationship between each pairwise relationship between stock markets.
- The DCC- beta (β) indicates long-run persistence. All the DCC β values are significant, which indicates the long-run persistence of every relationship between the stock market. So, investors should be cautious about investing in the long-run period as there is evidence of long-run persistence and they need to be convinced that the long-run relationships will offer the desired international diversification benefits.
- DCC-alpha (α) indicates short-run persistence. The table indicates the short-term persistence between UK-USA, UK-Germany, UK-India, UK-South Africa, Germany-India, Germany-South Africa, and India-South Africa relationship.

Our study further suggests that the investment professionals should rely more on the dynamic time-varying correlation among stock markets when choosing the composition of their portfolios rather than coefficient of correlations as the former is able to show dynamic market conditions.

CONCLUSION AND PRACTICAL IMPLICATIONS

This study evaluates the stock market's cointegration in the aftermath of COVID-19 and the investment implications using data from selected stock markets from January 2011 to December 2022. The sample period is further divided into three sub-samples pre-COVID, COVID and post-COVID periods to analyse the impact of COVID-19. We find stock returns for all selected markets are not normally distributed for the sample period. By applying the Pearson correlation matrix, we find that the stock markets are more correlated during the COVID period than during pre-COVID and post-COVID periods. Augmented Dickey-Fuller (ADF) and Zivot-Andrews tests for unit root indicate selected stock prices integrated at level one for all the sub-samples. The Gregory and Hansen cointegration test shows that 60% of the stock markets investigated have a long-run relationship before COVID. However, we found no stable long-run relationships among 80% of the stock markets investigated during post-COVID period. This means there are potential diversification benefits for investors who invested internationally among the sampled stock markets.

Further, we examine the time-varying correlation between stock markets using the DCC-GARCH model. We find clear evidence of an increasing correlation between the stock market during the COVID period. Furthermore, we find that there is a decrease in correlation post-COVID period. Theoretically, an external shock may increase the correlation between two stock markets and our finding confirms this as there was an increase in conditional correlation during COVID-19. The investment professionals, whom we presume to be active investors, should understand how markets cointegrate at normal times, during economic crises and after such crises as well as correlate in the design of their investment portfolios to fully benefit from international diversifications.

Our findings are sufficiently significant, and have important implications to investment professionals, policy makers and market regulators.

Firstly, our empirical study offers valuable insights into short-term and long-term investment. From the long-term investment perspective, the presence of cointegration among the selected stock market indicates that an investor cannot simultaneously reduce unsystematic risk by holding assets in those markets.

Secondly, we found the presence of a structural break from the visual properties of stock prices. As Gregory and Hansen (1996) mentioned, standard cointegration's power is reduced with the time series' structural break. Thus, ignoring the structural break during the cointegration analysis can lead to misleading results. Employing the Gregory and Hansen cointegration test to include the structural break into the analysis has led to a better understanding of stock market comovement.

Thirdly, the study's empirical results suggest mixed results from the Gregory and Hansen cointegration test where the number of pairwise cointegration decreased over time. So, investors can use this information to enhance their diversification benefits.

Fourthly, our study finds the dynamic conditional correlation among these stock markets has become more robust during the pandemic. In addition, we also find that COVID-19 influences stock prices and volatility significantly, leading international investors to withdraw their capital. Therefore, individual, and institutional investors diversifying their investment through global equity market investment should monitor the equity market closely to understand the stock market comovement.

Finally, while the regulators need to understand the market dynamics to improve market efficiency, the policymakers worldwide are interested in knowing the stock market comovement to maintain financial stability, our empirical findings can help both in their professional capacities to achieve success. If there are cointegration relations between the stock market, policymakers can take short-term steps to ensure market stability. At the same time, the comovement information can help investors and portfolio managers to make better asset allocation strategies.

There is still scope for further studies. This study can be extended to check the volatility spillover effect from Commodity markets in the stock markets. Over the last few years, the commodity market has fluctuated a lot—for instance, the price of oil. Evaluating the volatility spillover effect from the commodity market into the chosen stock market can provide further insights into the market and help policymakers make informed decisions.

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