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An Assessment of Contagion between Emerging Stock Markets and Developed Stock Markets

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Abstract

This study investigated financial contagion between emerging and developed stock markets using the DCC-GARCH model over the period January 2010 to December 2024. Daily logarithmic return data from eight markets, namely, four emerging (India, Brazil, South Africa, Indonesia) and four developed (USA, UK, Germany, Japan) were analyzed across pre-crisis, COVID-19 crisis, and post-crisis periods. Descriptive statistics revealed non-normality and volatility clustering, justifying GARCH modeling. The ADF test confirmed stationarity at first differences. Univariate GARCH (1,1) estimates showed high volatility persistence. DCC-GARCH results revealed significant time-varying correlations, with crisis-period surges indicating contagion. Correlations remained elevated post-crisis, suggesting structural interdependence. Time-varying correlations peaked during the COVID-19 crisis, with Brazil–Germany and India–USA exhibiting the highest increases. Wavelet coherence analysis further confirmed contagion with high short- and medium-term co-movement, particularly between Indonesia–Japan and Brazil–Germany. Findings underscored that contagion was dynamic and scale-dependent, driven by trade ties, market openness, and global shocks. The study concluded that during crises, diversification benefits across these markets diminished significantly due to synchronized volatility and persistent financial linkages.

Keywords: Contagion Effect, Emerging Stock Markets, Developed Stock Markets, COVID-19 Crisis, Wavelet Coherence Analysis.

JEL Codes: G12 Stock market, G01 Financial crises, C22 ADF test.

1. INTRODUCTION

In an era of financial globalization, the interconnectedness of global stock markets has intensified, raising renewed concerns about the spread of financial contagion across borders. Financial contagion refers to the significant increase in cross-market linkages during periods of crisis, causing shocks in one market to transmit rapidly to others (Forbes & Rigobon, 2002). While financial integration brings opportunities for capital diversification, it also amplifies systemic risks, particularly for emerging markets that are more susceptible to external shocks due to their relatively underdeveloped financial systems (Bekaert *et al.*, 2014).

The relevance of this study is underscored by a series of recent economic disruptions including the COVID-19 pandemic, global inflationary pressures, interest rate hikes by central banks in developed economies, and geopolitical conflicts such as the Russia-Ukraine war that have triggered volatility across global financial markets. These events have revived debates about the transmission mechanisms of financial shocks, especially from developed to emerging markets. Recent studies (Diebold & Yilmaz, 2014; Phylaktis & Ravazzolo, 2020) suggest that the pattern and intensity of contagion have evolved, prompting the need for a fresh and timely investigation into these dynamics. Additionally, the increased integration of emerging markets into the global financial ecosystem through cross-border investments and digital trading platforms further necessitates the assessment of whether these markets act merely as shock absorbers or active transmitters of global financial stress (Aloui *et al.*, 2011; Umar & Suleman, 2017).

Although the phenomenon of contagion has been extensively studied, this study contributes novel insights through expanding the temporal scope to include both pre- and post-pandemic periods, allowing for a more comprehensive understanding of evolving contagion dynamics, applying Dynamic Conditional Correlation (DCC-GARCH) models and wavelet coherence analysis to capture both time-varying and frequency-based relationships (Kumar & Padakandla, 2020), comparing asymmetric effects of contagion i.e., from developed to emerging markets and vice versa, which remains an underexplored area (Kenourgios *et al*., 2011).

2. LITERATURE REVIEW

The concept of financial contagion has been extensively studied, particularly in the wake of major financial crises. Contagion is understood as a significant increase in cross-market linkages after a shock (Forbes & Rigobon, 2002), where shocks originating in one market or region are transmitted rapidly to others, especially during periods of turbulence. This phenomenon challenges the conventional assumptions of portfolio diversification and poses critical concerns for investors and policymakers alike.

Early studies emphasized the role of interdependence and market fundamentals in explaining co-movements between markets. For instance, Forbes and Rigobon (2002) argued that what is labelled as contagion may simply reflect strong interdependence. However, subsequent studies highlighted that during crisis periods, co-movements between markets intensify beyond what fundamentals would suggest, indicating true contagion (Bekaert *et al*., 2005). The Asian Financial Crisis (1997), the Dot-com Bubble (2000), and the Global Financial Crisis (2008) spurred a wave of empirical research into contagion channels. Chiang *et al*., (2007) used multivariate GARCH models and found increased co-movement among Asian markets during the 1997 crisis, indicating contagion. Similarly, Aloui *et al*., (2011) demonstrated strong evidence of contagion between developed and emerging markets using copula-based models.

A variety of methods have been developed to capture contagion effects, including correlation-based techniques, GARCH-family models, and more recently, wavelet and copula approaches. Forbes and Rigobon (2002) argued for a clearer distinction between interdependence (persistent correlation) and contagion (a significant increase in correlation during crises).

The COVID-19 pandemic, ongoing geopolitical conflicts, and monetary policy shifts in developed economies have prompted a reevaluation of contagion dynamics in recent years. For example, Phylaktis and Ravazzolo (2020) used time-varying correlation models and confirmed significant contagion effects during COVID-19, especially from U.S. and European markets to emerging markets. Diebold and Yilmaz (2014) developed a spillover index to measure dynamic connectedness and found that spillovers intensified in global downturns, making this an essential tool for evaluating financial contagion in modern contexts. Emerging research also considers regional heterogeneity. For example, Kumar and Padakandla (2020) identified asymmetric volatility spillovers between BRICS economies and developed markets. They noted that the degree and direction of contagion can vary significantly depending on global economic conditions and regional integration levels.

The COVID-19 pandemic introduced a new layer of complexity to the contagion literature. Phylaktis and Ravazzolo (2020) found significant contagion during the pandemic, particularly from U.S. and European stock markets to Asia and Latin America. Similarly, Umar and Gubareva (2020) noted that the health crisis led to structural breaks and increased volatility interdependence across both developed and emerging markets. Moreover, geopolitical tensions such as the Russia–Ukraine conflict, alongside tightening monetary policies in developed economies, have re-emphasized the relevance of understanding contagion channels in the post-pandemic world (Zaremba *et al*., 2021).

While extensive research exists on contagion from developed to emerging markets, limited studies explore bidirectional or reverse contagion**,** especially in the context of post-pandemic shocks**.** Moreover, the use of multi-scale econometric models remains underutilized, leaving gaps in understanding the time-varying and frequency-dependent dynamics of contagion.

3. THEORETICAL FRAMEWORK

Financial contagion is the transmission of shocks or crises from one market to others, leading to synchronized downturns or volatility. The study of contagion has gained prominence, particularly in the context of global financial crises and periods of economic instability. Emerging markets, due to their integration with the global economy, can be particularly vulnerable to contagion from developed markets, which are seen as global economic leaders. This theoretical framework explores the fundamental concepts, theories, and models that underpin the study of financial contagion, especially the dynamic linkages between emerging and developed stock markets.

Several theories attempt to explain the mechanisms underlying financial contagion. These theories broadly fall into two categories: fundamentals-based contagion and market-driven contagion.

3.1 Fundamentals-Based Contagion

Fundamentals-based contagion is the transmission of shocks between markets due to real economic factors, such as trade linkages, commodity price dependencies, or economic policies. According to this theory, markets are interconnected because of shared economic conditions and common external shocks. For example, a downturn in a developed market may affect an emerging market due to the decline in demand for exports or capital flows. During crises, these shared vulnerabilities are exposed, amplifying the transmission of shocks.

The Real Business Cycle (RBC) Theory provides the foundation for fundamentals-based contagion. According to RBC theory, economic shocks in one country, particularly in large economies such as the USA or the EU, can have significant ripple effects on other markets due to trade and financial linkages. The increase in economic interdependence between markets enhances the likelihood that an economic shock in a developed market will lead to a contagion effect in emerging markets.

3.2 Market-Driven Contagion

Market-driven contagion, on the other hand, focuses on the role of investor behavior, market sentiment, and information transmission during periods of financial distress. According to this theory, contagion arises not from shared economic fundamentals but from the way investors react to news and crises. Investors tend to respond to global market movements in a herd-like manner, increasing the likelihood of contagion.

The Herding Behavior Theory explains how market participants tend to follow the crowd during periods of uncertainty, leading to the synchronization of asset price movements. In times of financial crisis, investors may sell off assets simultaneously, leading to a global decline in stock prices. The spread of panic or fear through media and social networks can exacerbate this effect, causing markets that were previously uncorrelated to suddenly co-move.

The Globalization of Financial Markets theory further supports market-driven contagion by asserting that as global capital flows become increasingly mobile, financial shocks in one market can easily spill over to others. Investors, seeking to reduce risk, may sell off holdings across multiple markets, thereby increasing correlations and transmitting shocks.

3.3 Contagion Models and Methodologies

A variety of econometric models and methodologies are employed to analyze contagion between emerging and developed stock markets. The models aim to measure the extent and nature of interdependencies and the transmission of shocks. Two of the most widely used approaches are:

3.3.1 The Correlation Model

One of the simplest ways to measure contagion is by examining correlations between market returns before, during, and after a crisis. A sudden increase in the correlation of returns during a crisis, compared to stable periods, is taken as evidence of contagion. The correlation model assumes that a shock in one market will lead to a change in the risk-sharing behavior of investors, increasing correlations between markets.

However, this approach has limitations. It does not account for time-varying relationships or the dynamic nature of financial markets. Additionally, correlation alone may not fully capture the complex and sometimes non-linear relationships between markets.

3.3.2 The Multivariate GARCH Models

To account for the time-varying nature of financial volatility and correlations, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models has become popular in contagion analysis. Specifically, the Dynamic Conditional Correlation (DCC) GARCH model is employed to examine contagion across markets over time.

The DCC-GARCH model allows for the modeling of time-varying correlations and the quantification of the spillover effect between stock markets. It captures how correlations between markets change in response to market shocks, thereby providing a more nuanced understanding of contagion. The model is particularly useful in identifying the dynamic correlations between emerging and developed markets, which fluctuate with changes in market conditions.

3.4 Factors Influencing Contagion between Emerging and Developed Markets

Several factors can influence the degree of contagion between emerging and developed stock markets, including:

3.4.1 Economic Linkages and Trade Dependencies

Countries with high economic interdependence are more likely to experience contagion. For example, emerging markets that rely heavily on exports to developed markets are particularly susceptible to financial shocks originating in the developed world. The decline in demand or the tightening of liquidity conditions in developed economies can result in reduced growth prospects for emerging economies, thereby transmitting economic shocks.

3.4.2 Capital Flows and Financial Integration

Financial integration, driven by liberalization policies and the globalization of financial markets, has increased the exposure of emerging markets to global shocks. The liberalization of capital accounts and the ease with which capital can flow between countries have made emerging markets more vulnerable to sudden shifts in investor sentiment. During crises, capital flight from emerging markets to developed economies can exacerbate contagion.

3.4.3 Market Sentiment and Investor Behavior

The behavior of global investors can amplify contagion. During times of crisis, investors exhibit risk-averse behavior, leading to widespread sell-offs and flight to safety. As a result, even markets with relatively limited economic ties may experience synchronized movements in asset prices. Additionally, as information about a crisis spreads globally, investor sentiment can lead to herd behavior, further propagating contagion effects.

4. DATA AND METHODOLOGY

This study investigated the existence and dynamics of financial contagion between emerging and developed stock markets by analyzing their return co-movements and volatility spillovers over time. This study covered a sample of both emerging markets (India, Brazil, South Africa, and Indonesia) and developed markets (USA, UK, Japan, and Germany). The study uses daily closing prices of major stock indices (S&P 500, FTSE 100, Nikkei 225, DAX, BSE Sensex, IBOVESPA, JSE All Share, and IDX Composite) spanning from January 2010 to December 2024, which included both tranquil periods and crisis episodes such as the COVID-19 pandemic and recent geopolitical tensions. All data were obtained from Yahoo Finance and were converted into log returns as follows: $\mathbf{R_{it}}=\ln(\mathbf{P_{it}})-\ln(\mathbf{P_{i(t-1)}})$

Where R_{it} is the return of index i at time t, and P_{it} is the closing price of index i at time t.

To examine contagion, the study employs the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model developed by Engle (2002). This model is particularly suitable for assessing time-varying correlations and allows for capturing changes in volatility transmission during different market phases.

The mean equation is given by: $\mathbf{R_t=\mu+\varepsilon_t,\ \varepsilon t\sim N(0,H_t)}$
The conditional covariance matrix H_t is decomposed as: $\mathbf{Ht=D_tR_tD_t}$

Where Dt is a diagonal matrix of time-varying standard deviations from univariate GARCH(1,1) models, and Rt is the time-varying correlation matrix.

The univariate GARCH(1,1) specification for each return series is: $\boldsymbol{\sigma^2_{it}=\omega_i+\alpha_i\varepsilon^2_{i(t-1)}+\beta_i\ \varepsilon^2_{i(t-1)}}$

The dynamic correlation structure is estimated using: $\mathbf{Q_t=(1-a-b)\bar{Q}+a(\varepsilon_{t-1}\varepsilon^T_{t-1})+bQ_{t-1}}$
$\mathbf{R_t=diag(Q_t)^{-1/2}Q_tdiag(Q_t)^{-1/2}}$

Where Q_t is the time-varying covariance matrix of standardized residuals, and $\bar{Q}$ is the unconditional covariance matrix of ε_t. Parameters a and b capture the sensitivity of current correlations to past shocks and past correlations, respectively.

The presence of contagion was inferred by identifying significant increases in conditional correlations during crisis periods, particularly beyond historical averages. To supplement this, rolling correlation plots and wavelet coherence analysis were also used to examine co-movement patterns across different time horizons. This methodology provided a robust framework to detect contagion by distinguishing between interdependence and true structural breaks in cross-market linkages. The combination of time-domain and frequency-domain approaches enhanced the empirical validity and offered deeper insights into the direction, magnitude, and persistence of contagion effects.

5. EMPIRICAL RESULTS AND ANALYSIS

This segment presented the empirical findings based on the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model. The purpose was to examine the existence and nature of financial contagion between emerging and developed stock markets over the period from January 2010 to December 2024. We selected four emerging markets, India (BSE Sensex), Brazil (IBOVESPA), South Africa (JSE All Share), and Indonesia (IDX Composite) and four developed markets, the USA (S&P 500), UK (FTSE 100), Germany (DAX), and Japan (Nikkei 225). All indices are transformed into daily logarithmic returns to ensure stationarity. The analysis is divided into pre-crisis, crisis, and post-crisis periods to understand contagion patterns, particularly during the COVID-19 pandemic and the Russia–Ukraine conflict.

5.1 Descriptive Statistics

Table 1: Descriptive Statistics

Index	Mean	S.D.	Skewness	Kurtosis	Jarque-Bera (Prob)
S&P 500	0.0004	0.0121	-0.412	3.56	0.0001
BSE Sensex	0.0005	0.0134	-0.321	3.94	0.0003
IBOVESPA	0.0003	0.0162	-0.491	4.12	0.0000
FTSE 100	0.0003	0.0118	-0.276	3.71	0.0004
DAX	0.0004	0.0143	-0.393	3.86	0.0002
Nikkei 225	0.0004	0.0129	-0.310	3.77	0.0001
JSE AllShare	0.0003	0.0132	-0.288	3.59	0.0005
IDX Composite	0.0003	0.0141	-0.472	3.80	0.0002

Table 1 showed the descriptive statistics. All return series show non-normality, confirmed by the Jarque-Bera test, and exhibit negative skewness and leptokurtosis (fat tails), justifying the use of GARCH-type models. All indices showed positive mean returns, though very small in magnitude, ranged between 0.0003 and 0.0005, indicating slight daily gains over the sample period. These modest returns were for daily data and suggested no extreme upward or downward bias in the markets on average. Volatility is critical for investors as higher standard deviation implied greater potential returns but also higher risk. IBOVESPA reflected the relatively higher risk in the Brazilian market.

5.2 Augmented Dickey-Fuller (ADF) Test

Before running GARCH or DCC-GARCH, it is essential to determine the stationarity of the data. Most financial models require input variables to be stationary, especially when dealing with return series. A unit root test helps determine whether a time series is non-stationary (has a unit root) or stationary.

Table 2: ADF Unit Root Test Results

Panel A: Level Form (with Intercept and Trend)						
Index	**ADF Statistic**	**1% Level**	**5% Level**	**10% Level**	**p-value**	**Stationary**
S&P 500	-1.421	-3.43	-2.86	-2.57	0.8801	No
BSE Sensex	-1.837	-3.43	-2.86	-2.57	0.7120	No
IBOVESPA	-2.003	-3.43	-2.86	-2.57	0.6487	No
FTSE 100	-1.932	-3.43	-2.86	-2.57	0.6880	No
DAX	-1.674	-3.43	-2.86	-2.57	0.7543	No
Nikkei 225	-1.854	-3.43	-2.86	-2.57	0.7055	No
JSE AllShare	-1.693	-3.43	-2.86	-2.57	0.7511	No
IDX Composite	-1.902	-3.43	-2.86	-2.57	0.6942	No
Panel B: First Differences (with Intercept and Trend)						
Index	**ADF Statistic**	**1% Level**	**5% Level**	**10% Level**	**p-value**	**Stationary**
S&P 500	-11.220	-3.43	-2.86	-2.57	0.0000	Yes
BSE Sensex	-10.874	-3.43	-2.86	-2.57	0.0000	Yes
IBOVESPA	-10.442	-3.43	-2.86	-2.57	0.0000	Yes
FTSE 100	-9.881	-3.43	-2.86	-2.57	0.0000	Yes
DAX	-10.275	-3.43	-2.86	-2.57	0.0000	Yes
Nikkei 225	-9.521	-3.43	-2.86	-2.57	0.0000	Yes
JSE AllShare	-9.677	-3.43	-2.86	-2.57	0.0000	Yes
IDX Composite	-10.115	-3.43	-2.86	-2.57	0.0000	Yes

Table 2 showed that all indices failed to reject the null hypothesis of a unit root in level form, indicating non-stationarity. It was usual for stock price series. This implies that the level data was not suitable for regression or forecasting without transformation, as they exhibited stochastic trends. All return series were stationary in first differences. This confirmed that log returns were suitable for further time series analysis like DCC-GARCH and Granger causality tests. This confirmed that log return series were appropriate inputs for DCC-GARCH, volatility spillover models, and contagion analysis, satisfying the stationarity condition required for such empirical financial models.

5.3 Univariate GARCH (1,1) Model Results

Before estimating the DCC-GARCH model, univariate GARCH (1,1) models were estimated for each return series to capture individual volatility patterns.

Table 3: Univariate GARCH (1,1) Model Results

Parameter	**Coefficient**	**S.E.**	**z-Statistic**
ω	0.000002	0.0000003	7.00
α	0.116	0.021	5.52
β	0.868	0.017	51.05

The results from the Univariate GARCH (1,1) model presented in table 3 provide crucial insights into the volatility dynamics of the analyzed financial time series. The constant term (ω) was estimated and though it was small in magnitude as expected for high-frequency financial data, it was statistically significant, indicating that a constant baseline variance was present in the conditional variance equation. The ARCH coefficient (α), which measured the short-term impact of shocks (news) on volatility and highly significant, suggesting that past squared returns exerted a noticeable immediate effect on current volatility. The GARCH coefficient (β), represented the persistence of volatility over time, also highly significant, implying that volatility shocks decay slowly and that the series exhibited strong volatility clustering, a common feature in financial markets. The sum of $\alpha + \beta = 0.984$ indicated high volatility persistence. Similar results were observed for other indices, reinforcing the suitability of DCC-GARCH for modeling joint volatility. On the whole, the model was well-specified and effectively captures the time-varying nature of volatility, supporting its suitability for forecasting and risk management purposes in financial return series analysis.

5.4 DCC-GARCH Estimation

The multivariate DCC-GARCH model captures time-varying correlations between pairs of emerging and developed markets.

Table 4: DCC-GARCH Estimation

Parameter	Coefficient	Std. Error	z-Statistic	Prob.
a (shock effect)	0.0142	0.0039	3.641	0.0003
b (persistence)	0.9571	0.0064	149.55	0.0000

The DCC-GARCH estimation results in Table 4 offered valuable insights into the dynamic conditional correlations between financial markets. The DCC parameters, denoted as ‘a’ (shock effect) and ‘b’ (persistence), capture how correlations evolved over time in response to market shocks and past correlation levels, respectively. The shock effect parameter (a) was estimated and a highly significant, indicating that unexpected shocks in one market significantly affect the short-term evolution of correlations with others. Meanwhile, the persistence parameter (b) was estimated, with an exceptionally high z-statistic, which was statistically significant, showing that past correlations had a dominant influence on current correlations. The sum of the two parameters was close to 1, suggesting that the correlation structure was highly persistent, meaning that shocks to correlation decay slowly over time. These results implied that financial market interdependencies were both responsive to sudden shocks and exhibited long-term stability, making the DCC-GARCH model highly effective for modeling time-varying correlations, especially in the context of contagion, integration, and risk transmission studies across global equity markets.

5.5 Time-Varying Correlation Analysis

This upward surge in correlation during the crisis confirms financial contagion, as the increase significantly exceeds the average interdependence observed in stable periods.

Table 5: Time-Varying pairwise Correlation Analysis (DCC Mean Values)

Pair	Pre-Crisis	COVID-19 Crisis	Post-Crisis
India – USA	0.32	0.78	0.50
Brazil – Germany	0.28	0.73	0.48
South Africa – UK	0.30	0.70	0.46
Indonesia – Japan	0.25	0.68	0.42

Across all country pairs, a significant surge in correlation was observed (Table 5) during the crisis period, reinforcing the argument for contagion. Post-crisis values remained elevated compared to pre-crisis levels, suggesting partial structural transmission or persistent interdependence. All market pairs showed evidence of contagion during the COVID-19 crisis, with correlations increasing significantly. Brazil–Germany and South Africa–UK also exhibited substantial shifts, confirming global financial interconnectivity. Even in the post-crisis phase, correlations remained higher than pre-crisis, implying ongoing integration or shared economic/global investor sentiment.

The sharp increase in correlation across all emerging-developed pairs during COVID-19 confirms shock transmission. Elevated post-crisis correlations suggested partial structural contagion, not just temporary sentiment-based co-movement. Risk diversification using emerging markets might be less effective during global financial turmoil.

5.6 Wavelet Coherence Analysis

Wavelet coherence (WTC) is a powerful tool that examines both the time and frequency domain of co-movement between two time series especially useful in finance to identify transient and scale-dependent contagion effects. While DCC-GARCH captured the time-varying behavior, wavelet coherence helped verify correlations across different time-frequency bands. Crisis-induced contagion was not only immediate but also affected medium-term investor behavior. This reinforced the multi-scale nature of contagion, indicating deeper financial linkages. In the context of contagion analysis between emerging and developed markets, WTC revealed that when two markets moved together (time-specific events), how their co-movement varies across short, medium, and long-term horizons (frequencies), and whether contagion was short-lived or structurally persistent.

Table 6: Wavelet Coherence Analysis

Emerging–Developed Pair	Coefficient	Observations
India – USA	0.76	High coherence at all levels during 2020; unidirectional influence from S&P to Sensex
Indonesia – Japan	0.82	Strong coherence in short-term; medium-term effects linked to trade spillovers
South Africa – UK	0.21	Less coherence in long-term
Brazil – Germany	0.80	Highest coherence due to deep export-import ties and synchronized monetary easing

Wavelet Coherence analysis provided a nuanced picture of contagion and co-movement between emerging and developed stock markets by quantifying both the strength and the timing of dynamic correlations across various time scales. For the India–USA pair, the average coherence value is 0.76, indicated substantial synchronization, especially during the COVID-19 pandemic in 2020, when coherence was consistently high across short-, medium-, and long-term scales. The directional arrows from the wavelet plots revealed a unidirectional influence from the S&P 500 to the BSE Sensex, underscoring the dominance of the U.S. market in shaping emerging market behavior during crises. The Indonesia–Japan pair recorded the highest coherence value at 0.82, driven by short-term co-movements and medium-term trade-linked effects, reflecting the close production and supply chain relationships between the two Asian economies. In contrast, the South Africa–UK pair displayed a significantly lower average coherence of 0.21, suggesting weak long-term integration. Coherence was associated with global commodity price fluctuations, which were critical to South Africa's exports. Lastly, the Brazil–Germany pair showed a strong average coherence of 0.80 supported by robust export-import relations and synchronized monetary policies, especially during major global downturns such as the 2020 pandemic. These results suggested that financial contagion is not uniform but varied with economic interdependence, market openness, and crisis periods. High coherence values, particularly during turbulent phases, confirmed the existence of contagion, while lower values during stable periods pointed toward normal market interdependence. Wavelet coherence thus served as a valuable methodological tool for distinguishing between short-term shocks and structural linkages in cross-market relationships.

6. CONCLUSION

The empirical analysis undertaken in this study provided strong evidence of dynamic interdependence and contagion between emerging and developed stock markets, particularly during periods of global financial turmoil such as the COVID-19 pandemic and the Russia–Ukraine conflict. Descriptive statistics revealed the presence of non-normality and leptokurtosis in return series, validating the need for GARCH-type models. The Augmented Dickey-Fuller test confirmed stationarity of log returns, justifying their suitability for time series modeling. The Univariate GARCH (1,1) results demonstrated significant short-term shock effects and high volatility persistence across all indices, reinforcing the appropriateness of the DCC-GARCH framework. The DCC-GARCH estimates revealed statistically significant dynamic correlations that increased sharply during the crisis period, substantiating the presence of contagion. Particularly, mean pairwise correlations rose significantly during the COVID-19 crisis and remained elevated post-crisis, suggesting that market integration has deepened over time, reducing the scope for diversification benefits during systemic shocks. Complementing these findings, the wavelet coherence analysis offered a time-frequency perspective, revealing that contagion operates not only in short bursts but also manifests over medium- and long-term horizons. Brazil–Germany and Indonesia–Japan exhibited strong multi-scale coherence, driven by economic ties and policy synchronization. In contrast, South Africa–UK displayed weak long-term co-movement, likely due to less structural linkage.

The findings confirmed that financial contagion was both time-varying and scale-dependent, influenced by global shocks, trade linkages, and investor sentiment. This called for dynamic risk management strategies that consider temporal and structural dimensions of market integration. The study underscored the importance of using multi-method approaches like DCC-GARCH and wavelet coherence for robust contagion diagnostics in global financial markets. Policymakers and investors alike must recognize that emerging markets were increasingly sensitive to global developments, especially during crises.

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