Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 9375170, 16 pages
https://doi.org/10.1155/2022/9375170

Research Article

Diversification Benefits between Stock Returns from Ghana and Jamaica: Insights from Time-Frequency and VMD-Based Asymmetric Quantile-on-Quantile Analysis

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Received 6 June 2022; Accepted 11 July 2022; Published 10 September 2022

Academic Editor: Yuxing Li

Due to the susceptibility of assets to the dynamism in financial markets, the emergence of new asset classes induces empirical assessments of their risk-reduction abilities. This issue is envisaged from the perspective of new investment combinations that emerge from the new market alliance between Ghana and Jamaica. This study investigates the heterogeneous and asymmetric co-movements between stock market returns from Ghana and Jamaica with data from 04 April 2011 to 17 March 2022. The wavelet analysis is carried out, followed by causality in quantiles and quantile-on-quantile regression (QQR) analysis with decomposed return series using the variational mode decomposition (VMD) approach. The findings from the bi-wavelet analysis divulge low connectedness between stock returns from Ghana and Jamaica. The cone of influence from the coherence plot does not cover the entire spectrum, particularly beyond the annual scale. Hence, co-movements between GSECI and JSEIND beyond a year may be less significant for portfolio management. Findings from the causality test evidenced bi-directional asymmetric causality between the two markets. From the VMD-based QQR analysis, it is revealed that stock returns from Ghana and Jamaica are safe-havens, hedges, and diversifiers for each other. The significant diversification prospects between the two markets signal that the two stock markets could facilitate the inflow of capital assets for extended growth and development of their overall economies. Policymakers and regulators could attract international investors and promote the flow of funds between the two economies through effective regulation of stock markets. Specific implications for market participants and policymakers are discussed.

1. Introduction

The attraction of capital flows to facilitate sustainable economic growth has recently appealed to some developing and developed economies. One sure channel of attracting high capital flows is building a resilient stock market [1]. Through financial market integration, investors are attracted to assets from overseas markets. This calls for strengthening of ties and realigning interests to facilitate the regulation of stock and other financial markets which could boost the process towards the achievement of economic growth by attracting all classes of investors. Despite the advantages associated with financial market integration, portfolios stand the risk of losing diversification advantages. Hence, in as much as advantages may accrue from new market alliances, the need to examine the co-movement of assets from those markets cannot be overlooked. This explains why the emergence of new asset classes induces empirical assessments of their risk-reduction abilities [2]. Such empirical investigations are critical due to the susceptibility of assets to the dynamism in financial markets [3–5]. This issue is envisaged from the perspective of new investment combinations that emerge from the new market alliance between Ghana and Jamaica.

On May 10, [6] Business and Bossman et al. [7] reported that the stock markets of Ghana (i.e., Ghana Stock Exchange(GSE)) and Jamaica (Jamaica Stock Exchange (JSE)) had signed a momentous Memorandum of Understanding (MoU) which is projected to strengthen the partnership between the two stock markets and their respective economies. The MoU is the first of its kind involving a Caribbean stock market and given the mutual characteristics ("Ghana and Jamaica alike have a growing and educated middle class with high demand for services" [6]) they share; it is further expected that the MoU attracts huge investments between them and also draws on international investors to the respective economies. However, what this partnership means to investors, practitioners, and policymakers is not known and must be empirically examined.

Notable questioning themes that need to be addressed to aid asset allocation and investment decisions among market participants and also guide regulators and policymakers include

(i) What has been the fundamental relationship between the GSE and JSE?

(ii) Do the stock market returns from GSE co-move with their JSE counterparts?

(iii) Does the co-movement between GSE and JSE differ across investment horizons?

(iv) What is the relationship between stock returns from GSE and JSE across the bullish, average, and normal market conditions?

To provide rigorous responses to these questioning themes, this study examines the time-frequency co-movements between the stock market returns from Ghana and Jamaica. It is important to note that, in line with the fractal market hypothesis [8], market participants' response to various market dynamics is heterogeneous [9, 10]. Similarly, the adaptive markets hypothesis [11] explicates that, as markets undergo structural changes, investor responses tend to align with such changes.

In [12], therefore, it is unnatural that, in a typical financial market, static relationships are assumed. Furthermore, asymmetries and nonlinearity are ingrained features of financial and economic time series [4, 7, 13, 14], suggesting that when signals (original data) are not delineated into their various modes, tested relationships may produce biased results. This brings to light the essence of conducting analysis in data decomposition-based frameworks.

Accordingly, this study examines the time-frequency and asymmetric connectedness between the stock market returns of GSE and JSE under decomposition-based paradigms. The study contributes to the body of knowledge as follows.

First, this study provides a first-hand empirical response to essential questions that would rightly inform asset allocation and effective management of portfolio risks. The connection between assets or markets is needed by investors to influence how funds are distributed across Ghanaian and Jamaican stocks. Similarly, regulators would be informed of the nature of the linkages between GSE and JSE. Such information is necessary to guide policymakers from the two markets to align their interests when devising mutual policies for the respective stock markets.

Second, knowledge about the connectedness between the two stock markets is nonexistent, either in prior crisis periods or in recent systemic crises and geopolitical tension periods. As a result, the study employs a long dataset as far as availability permits, to provide insights into how GSE and JSE stocks co-move in past and current periods characterised by turbulence. Not only is this analysis conducted in average trading periods, but the dynamics of the relationship between the two markets are also analysed across the short-, medium-, and long-term trading periods. This is essential to market participants who adjust their investment decisions across various trading horizons.

Third, in terms of methods, the wavelet coherence and the variational mode decomposition approaches are employed. The outputs from wavelet decomposition are revealed in the resultant phase difference and coherence plots and form one aspect of the study's analysis. The outputs from the VMD are used as inputs to first establish causality between the two markets–GSE and JSE across different quantiles using the causality in quantiles approach. Unlike the traditional Granger causality that shows average causality, the causality in quantiles enables the testing of how the independent variable causes the dependent variable across different quantiles of the dependent variable. The next analysis is carried out using the quantile-on-quantile regression (QQR) approach, which allows one to examine the relationship between the dependent and independent variables across different quantiles of both variables. By this analysis, the relationship between the two assets is revealed for bullish, normal, and bearish market states. Outputs from the VMD also serve as the inputs for the QQR analysis.

To the best of the author's knowledge, no single study examines the connectedness between Ghanaian and Jamaican equities using the aforementioned approaches. It is worth noting that these econometric approaches are combined in this study due to their merits. For the studied assets, the wavelet coherence approach reveals their lead-lag behaviour, which is particularly relevant for devising trading strategies and timing investment decisions [15]. However, in as much as this feature rests well with the technique in a time-frequency paradigm, it is unable to ascertain the asymmetric relationships between the studied assets. As a result, the QQR analysis is additionally introduced to ascertain how one asset responds to the other across different market conditions (normal, bullish, and bearish).

Furthermore, the use of signal data may result in biased conclusions due to the susceptibility of fluctuating signals that may give rise to nonstationarity distributions. Besides, the use of signal data in QQR analysis cannot unveil the asymmetric effects in their respective modes that may correspond to the short-, medium-, and long-term dynamics. Based on the above reasons, the VMD approach is employed to generate additional inputs for the QQR analysis. As a precondition to the QQR analysis, the nonlinear causal effect between the studied assets needs to be ascertained. This is achieved using the causality-in-quantiles approach, which does better than the classic Granger-causality test. Unlike the classical Granger causality, which only tests average (mean) causality, the causality-in-quantiles test works well across distinct quantiles of the dependent variable [4, 14].

Overall, the application of these techniques is essential for rigorous analysis of the economic and practical implications of the partnership between the stock markets of

Ghana (GSE) and Jamaica (JSE). Findings from the bi-wavelet analysis suggest that stock market returns from the GSE significantly drive their JSE counterpart in the long-term (annual scale) during stressed market periods. The short- and medium-term leave behind no consistent driver of market returns. Meanwhile, the results from the causality in quantiles evidence the asymmetric bi-causality between market returns from GSE and JSE. The QQR analysis indicates that across the lower (median) quantiles, market returns from GSE and JSE are safe-haven (hedges) for each other. At worse, market returns from GSE are JSE diversifiers for each other.

In the remaining sections, Section 2 describes the dataset and details the econometric methods; the main findings are discussed in Section 3; implications of the results are discussed in Section 4, and Section 5 concludes the study.

2. Data and Methods

2.1. Data. The data comprise daily stock market indices for the Ghana Stock Exchange Composite Index (GSECI) and the Jamaica Stock Exchange Index (JSEIND) from 31 December 2010 to 17 May 2022. All data were sourced from the database of EquityRT. The sample period is influenced by the availability of data for both stock markets. The data on GSECI are available from 31 December 2010 and, hence, determined the start date of the sample period. Maintaining common data points, the return series yielded 2740 observations from 04 January 2011 to 17 May 2022. Trends of the various stock market data are shown in Figure 1.

From the raw series in Figure 1 (plot A), it could be observed that the Jamaican stock market is highly capitalised relative to the Ghanaian market. The capitalisation of the GSECI overtook that of the JSEIND in 2014 but after overtaking the GSECI in 2015, the JSEIND continues to dominate. It is worth noting that the sharp drop in JSEIND's capitalisation during the early days of the COVID-19 pandemic was more intense than that of GSECI. Plots B (Ghana) and C (Jamaica) from Figure 1 detail the return series plots for the signal (original data) and the modal decompositions-M1, M2, M3, and MAgg. The statistical properties of the data are detailed in Table 1.

The mean returns from the GSECI were negative over the period but that of JSEIND was positive. While GSECI recorded its maximum returns of more than 17%, JSEIND's maximum returns over the sample period were below 8%. Notwithstanding, negative returns were higher for GSEI (>18%) relative to the negative returns for JSEIND (<6%). The negative skewness for Ghana indicates that more negative returns were realised over the period whereas the opposite holds for Jamaica. The kurtosis statistics depict a leptokurtic behaviour for the return series, but in higher magnitude for Ghana. Whilst the data series rejects normality, their stationarity property is confirmed by the ADF and PP statistics. These statistics averagely suggest that the JSEIND performs better than the GSECI. Thus, Ghana stands the chance to benefit greatly from the new MoU. The correlation matrix (panel B) indicates a low unconditional correlation between stock returns from Ghana and Jamaica.

2.2. Methods

2.2.1. Bi-Wavelet. From a continuous wavelet transform (see Agyei et al. [16], for the full steps of the continuous wavelet transform), the covariance in the time-frequency domain described by the cross-wavelet transform is given as

$$W_{xy} = W_x(i,s)W_y^*(i,s), \tag{1}$$

where the cross-wavelet of the series $x(t)$ and $y(t)$ are, respectively, represented by $W_x(i,s)$ and $W_y^*(i,s)$ and $*$ is an indication of a compound conjugate. The area in the time-space possessing common power to a higher degree is shown by the cross-wavelet transform.

Following Grinsted et al. [17], a befitting expression for the WTC is the square of the absolute value of a normalised wavelet cross-spectrum proportionate to a single wavelet power spectrum. Consequently, an expression for the square of a wavelet coefficient is provided in equation (2) as

$$R^2_{(x,y)} = \frac{\left|\rho\left(s^{-1}W_{xy}(i,s)\right)\right|^2}{\rho\left(s^{-1}\left|W_x(i,s)\right|^2\right)\rho\left(s^{-1}\left|W_y(i,s)\right|^2\right)}, \tag{2}$$

where a smoothing factor that ensures a balance in resolution and significance is indicated by ρ, and the resultant value of the square of the wavelet coefficient, R^2_{xy}, is such that $0 \le R^2_{xy}(i,s) \le 1$. By interpretation, weak relationships are indicated by values approaching 0 whereas strong relationships are indicated by values approaching 1. Wavelet analysis reveals the wholistic co-movement between frequency-domain and time-frequency series. Hotter colours are revealed for stronger dependencies or correlations and mild colours are for weaker correlations.

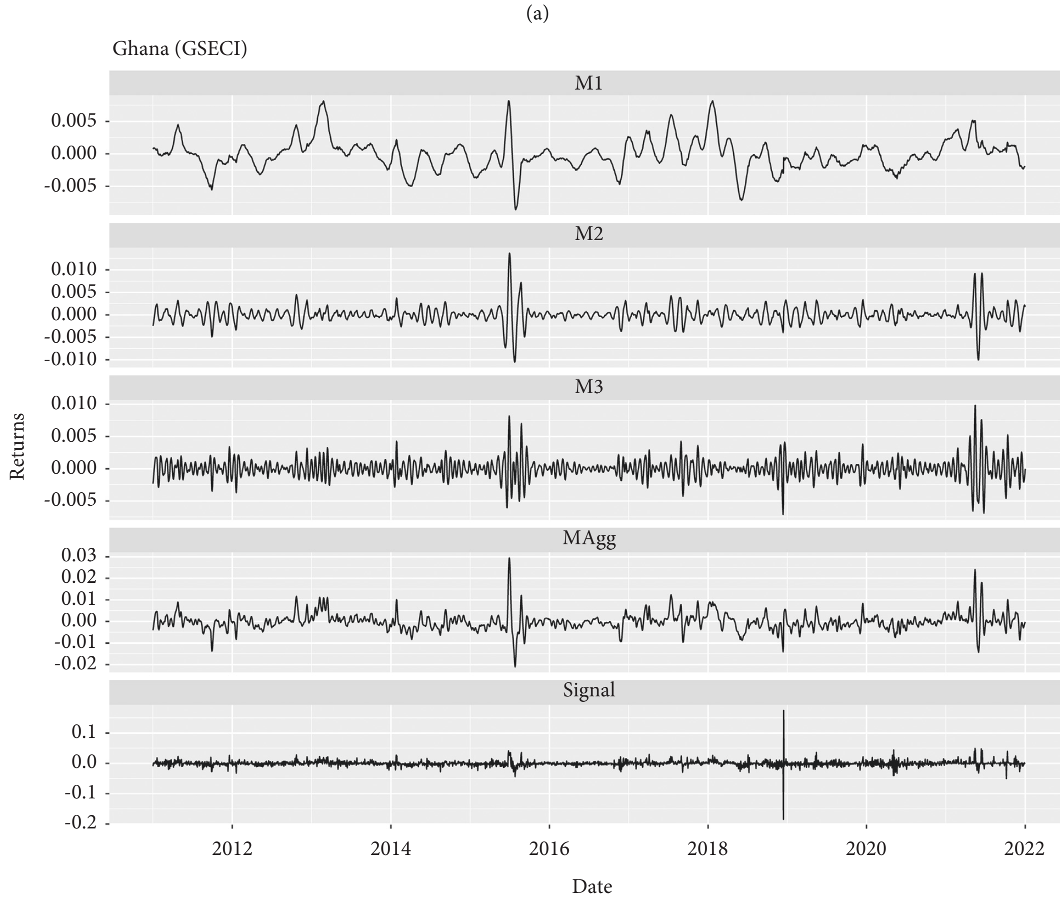
2.2.2. Variational Mode Decomposition (VMD). Following Dragomiretskiy and Zosso [18], the k_{th} mode $u_k(t)$ is expressed as

$$u_k(t) = A_k(t)\cos\left(\phi_k(t)\right), \tag{3}$$

where $A_k(t)$ is the instant amplitude, $\phi_k(t)$ is the instantaneous phase, and its derivative $\omega_k(t) = \phi_k\ (t)$ denotes the instant scale.

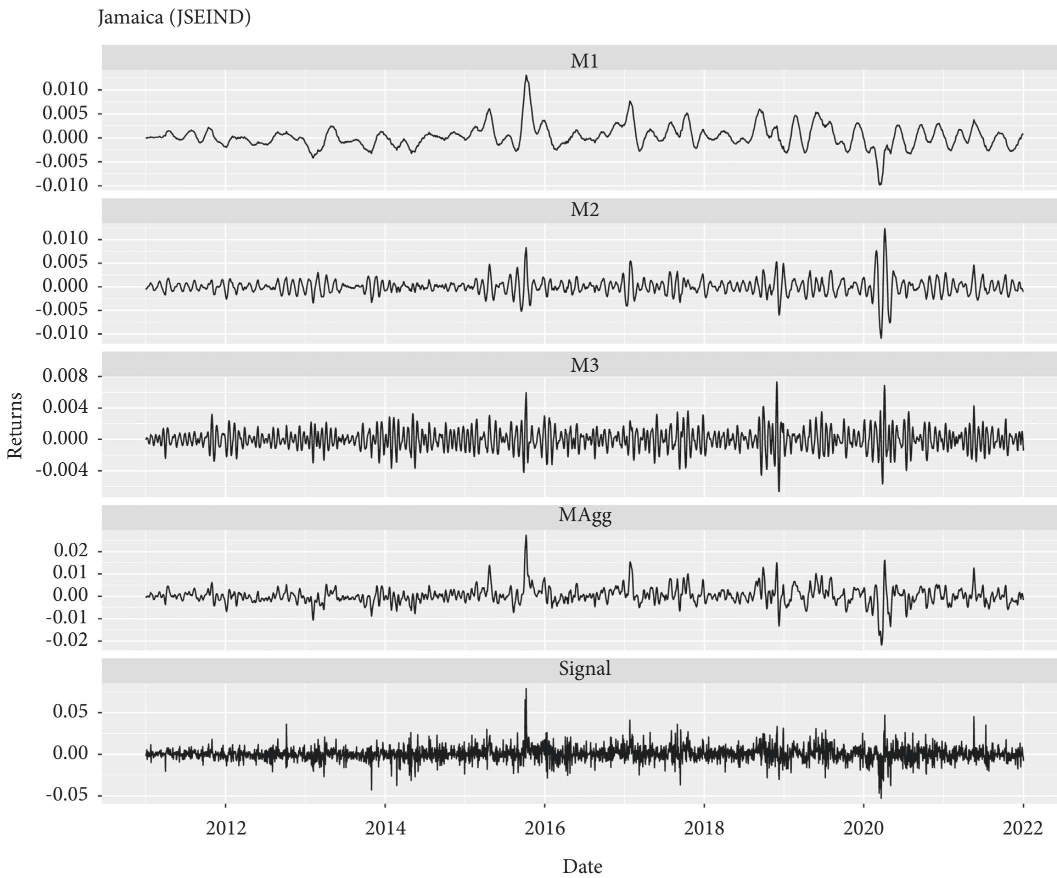
The VMD produces, for every mode $u_k(t)$, the logical signal and approaches the independent frequency spectrum using the Hilbert transform. Using the displacement property of the Fourier transform, a relocation to the baseband of the mode's spectrum is made. Next, the bandwidth is proposed by the H^1 Gaussian smoothness. There is an optimisation whose existence is to minimise the addition of the entire spectral widths of the mode functions to an infinitesimal value as Hashmi et al. [19] and Hamilton et al. [20]:

(a)



(b)

FIGURE 1: Continued.



(c)

Figure 1: Trajectories of stock market indices and returns. Notes: this figure displays the trajectory of the raw series (plot A) and returns series (plots B for Ghana and C for Jamaica) for the Stock Exchanges of Ghana and Jamaica. GSECI is the Ghana Stock Exchange Composite Index and JSEIND is the Jamaica Stock Exchange Index. Raw indices/returns are plotted against the y-axes.

Table 1: Descriptive statistics and correlation matrix.

Panel A : Sample statistics	Ghana (GSECI)	Jamaica (JSEIND)
Observations	2740	2740
Min	−0.1844	−0.0528
Max	0.1750	0.0788
Median	−0.0001	0.0002
Mean	−0.0002	0.0003
Std. dev	0.0090	0.0088
Skewness	−0.2470	0.3815
Kurtosis	118.0771	6.4888
Normtest.W	0.6989***	0.9368***
ADF	−15.7822***	−16.2129***
PP	−58.8697***	−55.9105***
Panel B : correlation matrix		
Ghana	1.0000	
Jamaica	0.0081	1.0000

Notes: this table presents the descriptive statistics of the daily stock market data for Ghana and Jamaica in Panel A. Panel B presents the unconditional correlation between the two markets' returns. ADF is the Augmented Dickey–Fuller test and PP is the Phillips–Perron test.

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_{k=1}^{k} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\},$$
$$s.t. \sum_{k=1}^{k} u_k = f, \tag{4}$$

where $\{u_k\}$ is mode ensemble, $\{\omega_k\}$ is the comparable centre frequency ensemble, and K is the mode observation (for a detailed presentation of the technique, see Adjei et al. [21]). Hamilton and Ferry's (2017) package "VMD" contains the VMD code.

2.2.3. Causality in Quantiles. To empirically prove bi-directionality for the stock-bond interrelation in this study, the causality-in-quantiles test of Jeong et al. [22] improved by Balcilar et al. [23] is employed. Thus, the study follows Balcilar et al. [23] to establish causality in means and variances, using the nonparametric Granger-quantile-causality technique. In simplified terms, we test the null hypothesis, H_0, as

$$H_{0A}\text{: GSECI returns do not Granger JSEIND,}$$
$$H_{0B}\text{: JSEIND returns do not Granger GSECI.} \tag{5}$$

In each stock market, the hypothesis for the quantile causality test statistic is tested at the 5% level of significance. Plots of the t-statistics across all quantiles for GSECI and JSEIND are presented. The study shows that the GSECIJSEIND interrelation (Figure 2) is bi-directional.

2.2.4. Quantile-on-Quantile Regression (QQR). Sim and Zhou's [24] QQR technique is used to investigate the wholistic interlinkages between GSECI and JSEIND. The QQR model is a more advanced variant of the basic quantile regression (QR) that is created by mixing nonparametric estimations with basic QR. The influence of the regressors across multiple quantiles and the conditional mean of the regressand, are investigated using conventional quantile regression [14, 25]. As a consequence, the QR approach outperforms the ordinary least squares (OLS) approach. Traditional linear regression developed by Stone [26] and Cleveland [27] evaluates the influence of certain quantiles of the explanatory variable on the conditional average of the explained variable [19]. As a result, the influence on different quantiles of both the explanatory and explained variables can be examined by combining classic linear regression with basic quantile regression. This offers a better understanding of how the explanatory and explained variables interact.

In this study, the impact of diverse GSECI quantiles on diverse quantiles of JSEIND returns is examined using an expanded method and termed the QQR approach developed by Sim and Zhou [24]. The nonparametric QR models specified in equations (6) and (7) are used for this purpose:

$$\text{GSECI}_t = \beta^{\theta}(\text{JSEIND}_t) + u_t^{\theta}, \tag{6}$$

$$\text{JSEIND}_t = \beta^{\theta}(\text{GSECI}_t) + u_t^{\theta}, \tag{7}$$

where GSECI_t is the stock returns from GSECI at time t, JSEIND_t is the stock returns from JSEIND at time t, β^{θ} is the slope of the relationship between GSECI_t and JSEIND_t, θ represents the θ^{th} quantile distribution of either GSECI or JSEIND, and u_t^{θ} is the quantile error term.

Note that when using the nonparametric approach, selecting the appropriate bandwidth is critical. A large bandwidth h grows the estimate's deviation while the variance decreases, and vice versa. Following Sim and Zhou [24], a bandwidth value of $h = 0.05$ is specified.

3. Empirical Results

This section presents the main findings of the study. The results are presented in three parts. The first part deals with the time-frequency co-movements between stock returns from GSECI and JSEIND; the second part entails the analysis of the causality in quantiles and lays the foundation for the third part, which covers the quantile-on-quantile analysis across frequencies.

3.1. Analysis of Co-Movements between Returns of GSECI and JSEIND. Together with the cone of influence (COI), Figure 3 shows the phase difference as graphical presentations, also known as scalograms, using the bivariate wavelet technique. For comparison, the phase difference is presented along with the coherence plot. The scalograms' horizontal axis depicts the data series' historical time, while the vertical axis depicts periodicity (i.e., frequency) bands. The frequency bands are often interchanged with time scales in practical interpretations, with high frequencies representing lower scales and lower frequencies representing higher scales (in respect of the scale, 2, 4, and 8 are termed as lower time-scale bands which are equivalent to higher periodicity or frequency band of 2~4 days and 4~8 days (weekly scale). The 16^{th}, 32^{nd}, 64^{th}, and 128^{th} scales correspond to the intermediate term with frequency band 16~32, 32~64, and 64~128 days (monthly, quarterly, and semi-annual), and the higher scale (long-term horizon) of 128~256 and 256~512 days, respectively, represent semi-annual to annual, and biennial). The COI represents the zone for the edge effect such that beyond this point inferences based on estimated correlation coefficients or coherencies become shaky. Furthermore, significant coefficients (the statistical significance of coefficients is calculated using Monte Carlo simulation techniques within a 5% significance bound) with positioning arrows indicate the relationship's direction (if the positioning arrows point right, the pair of data series is directly/positively correlated (in-phase); if the arrows turn left, the pair is inversely/negatively linked (anti-phase). If arrows position either right-up or left-down, the GSECI leads and lags if arrows point either right-down or left-up. If positioning arrows turn straight-upward (straight-downward), the GSECI data series is in the lead (lag) position) are restricted inside the zone's white outlines for edge effect. The phase difference plot (i.e., plot B) reveals areas where significant co-movements tend to occur, and these are pictorially shown in the coherence plot (i.e., plot A).

Across the higher and intermediate periodicity frequency bands (i.e., at lower and medium scales of 2~64 days), the coherence plot shows interspersed positioning arrows scattered across the scalogram and hardly depicts any consistent order of relationship between the stock returns from the two markets. This may be attributed to the behaviour of market participants in the short term. The short term is characterised by several transitory events that may cause dismays if not carefully analysed by market participants [4]. This explains why the positioning arrows hardly exhibit any consistent pattern that could facilitate risk management.

In the medium- (scale 64~128 days, which corresponds to quarterly to semi-annual) and long-term (scale 128~256 days, which corresponds to annual scale) periods, the scalogram shows positioning arrows that consistently evidence the leading (lagging) role of GSECI (JSEIND) returns. Thus, stock returns from GSECI drive their counterparts from the JSEIND. Impliedly, for any shocks to the Ghanaian stock market, the Jamaican stock market would most likely follow. It must be noted that this relationship occurs in calendar periods that correspond to key

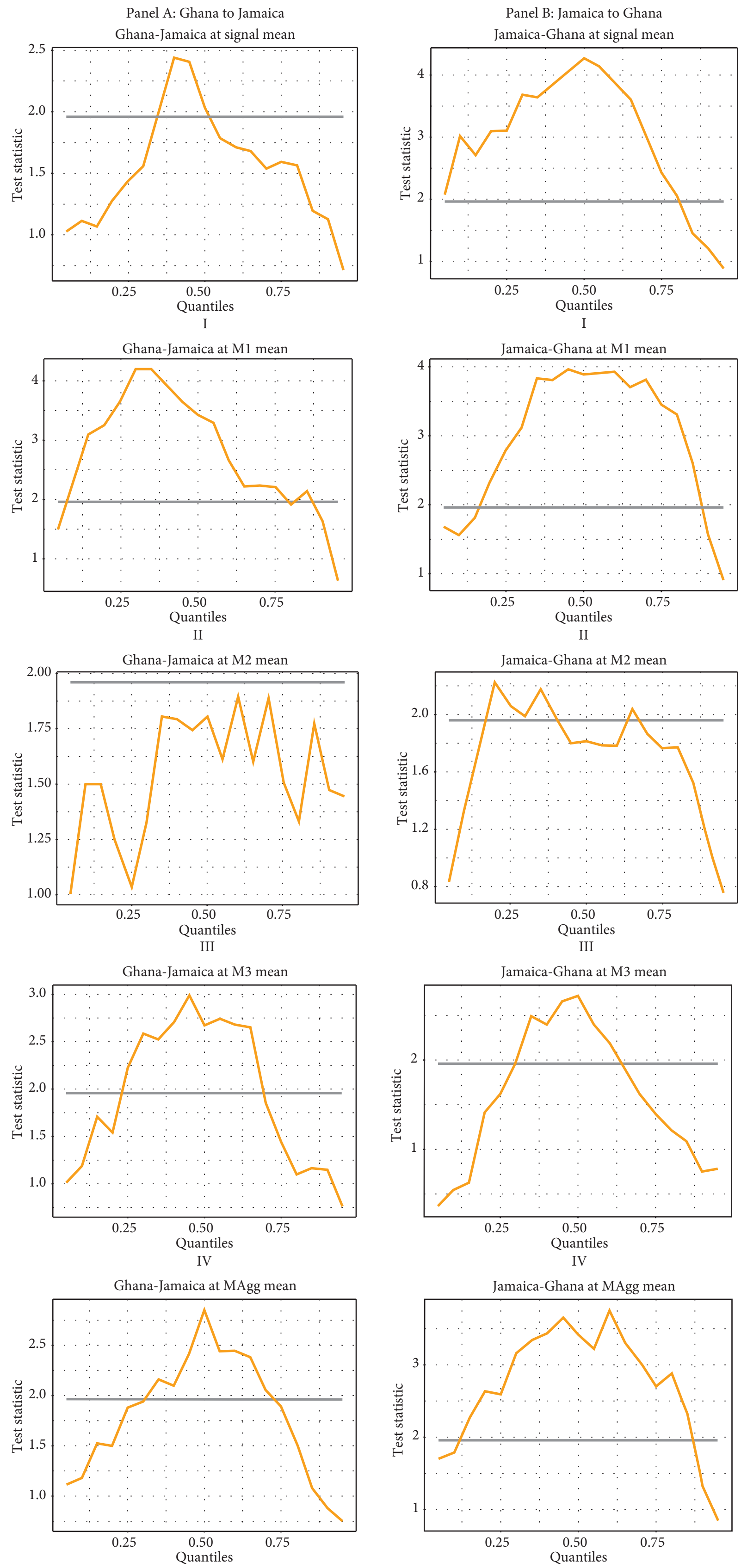
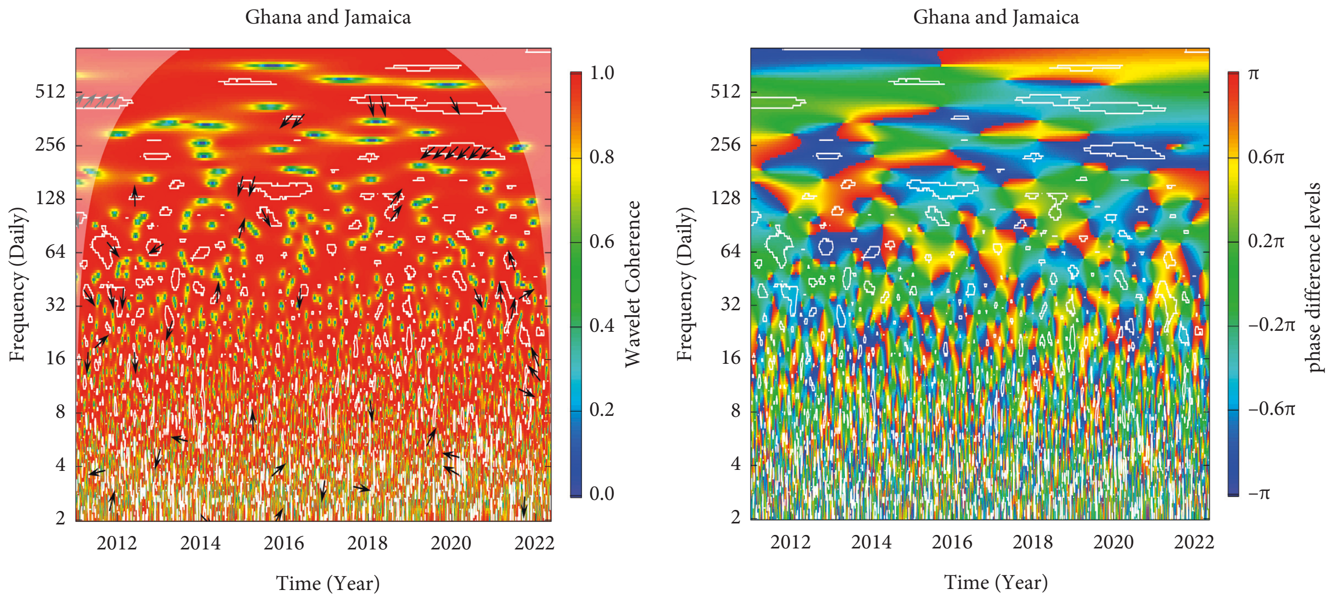


Figure 2: Plots of test statistics for causality in quantiles. (a) Panel A : Ghana to Jamaica. (b) Panel B : Jamaica to Ghana. Notes: this Figure presents the plots for the t-statistics across quantiles. Signal represents the original series and M1-M3 and MAgg are the resultant series from the VMD. For each plot, the t-statistics are plotted against the vertical axis and the quantiles are shown on the horizontal axis. Panel A (left) shows the causality in quantiles for the relationship "Ghana- > Jamaica" and Panel B (right) shows the causality in quantiles for the relationship "Jamaica- > Ghana."



(a) (b)

Figure 3: Wavelet coherence plots. Notes: this figure presents the wavelet coherence plot between the returns on GSECI and JSEIND (plot A) from 04/01/2011 to 17/05/2022. Plot B shows the phase difference for the wavelet detail between GSECI and JSEIND.

crisis events. Since the medium term is characterised by key events [28], connected markets would respond to shocks similarly. Beyond the 256 frequency band (256–512 and 512–1024 days), the scalogram reveals no significant co-movement except for a few spots in 2016, 2019, and 2020, which indicate some prospects for either market to lead the other. It is important to note that the COI does not cover the entire spectrum, particularly beyond the annual scale. Hence, co-movements between GSECI and JSEIND beyond a year may be less significant for portfolio management.

An essential observation from the wavelet coherence analysis indicates that there are significant causal linkages between the two markets (GSECI and JSEIND). Although in the time and frequency domains, these linkages have been shown by the wavelet coherence plot; we are unable to determine the specific market state(s) in which the linkages occur. Knowing the market condition in which assets are connected is equally important as knowing the degree and direction of connectedness between them. This helps to identify safe-havens and hedges for portfolio diversification. Hence, to ascertain the relationship(s) between the returns from the two markets across market conditions, the quantile regression analysis is employed. To equally reveal these conditional relationships across the frequency domain (i.e., trading periods), the VMD-generated modes (M1, M2, M3, and MAgg) are used as inputs for the analysis.

3.2. Analysis of Causality in Quantiles. Before examining the quantile relationships between the returns of GSECI and JSEIND, it is necessary to empirically ascertain whether or not the two assets cause each other across quantiles. The causality in quantiles tests the hypothesis that (i) GSECI *returns do not Granger* JSEIND and (ii) JSEIND *returns do not Granger* GSECI. To reject the null, a test statistic of each estimate should be at least 1.645 for a 90% confidence interval (CI), 1.96 for a 95% CI, and 2.567 for a 99% CI. By default, the estimates are tested at the 95% CI, which is depicted by a thick black horizontal line in each plot of Figure 2. To ascertain bi-causality, the causality in means test was carried out for Ghana causing Jamaica (Ghana- > Jamaica) and Jamaica causing Ghana (Jamaica- > Ghana). This was carried out for the signal data as well as the VMD-based decomposed series M1, M2, M3, and MAgg to represent the short-, medium-, long-term, and residue. The results, i.e., the test statistics, from the causality in quantiles test for both relationships–Ghana causing Jamaica (Ghana- > Jamaica) and Jamaica causing Ghana (Jamaica- > Ghana) are numerically (pictorially) shown in Table 2 (Figure 2).

For the signal data, the results (Table 2 and Figure 2) show that bi-directional causality is established between Ghana (GSECI) and Jamaica (JSEIND). In the case of Ghana- > Jamaica (Jamaica- > Ghana), the hypothesis of no causality is rejected ($t > 1.96$; $p < 0.05$) at within the quantile range 0.35–0.60 (0.05–0.80). At M1, the hypothesis is rejected ($t > 1.96$; $p < 0.05$) in the case of Ghana- > Jamaica across the quantiles 0.10–0.85 and 0.20–0.85 for Jamaica- > Ghana. For M2, the hypothesis largely supported ($t < 1.96$; $p > 0.05$) under a 95% CI in the case of Ghana- > Jamaica across all quantiles but rejected ($t > 1.96$; $p < 0.05$) across the quantile range 0.15–0.40 and 0.65 for Jamaica- > Ghana. For M3, the hypothesis is rejected ($t > 1.96$; $p < 0.05$) in the case of Ghana- > Jamaica across the quantile range 0.25–0.65 and 0.30–0.60 for Jamaica- > Ghana. For MAgg, the hypothesis is rejected in the case of Ghana- > Jamaica across the quantile range 0.30–0.70 and 0.20–0.85 for Jamaica- > Ghana.

The results affirm that the returns of GSECI cause the returns of JSEIND across the quantiles of JSEIND or GSECI,

Table 2: Test-statistics from causality in quantiles' tests.

Dir. τ	Ghana -> Jamaica	Jamaica -> Ghana	Ghana -> Jamaica	Jamaica -> Ghana	Ghana-> Jamaica	Jamaica-> Ghana	Ghana -> Jamaica	Jamaica -> Ghana	Ghana -> Jamaica	Jamaica -> Ghana
	Signal		M1		M2		M3		MAgg	
0.05	1.02608	2.06921**	1.48828	1.67655*	1.00243	0.83153	1.01186	0.36135	1.11381	1.70444
0.10	1.11178	3.02353***	2.31957**	1.56476	1.50123	1.33547	1.18772	0.54498	1.17734	1.78886
0.15	1.06679	2.70409***	3.10621***	1.81047*	1.49842	1.76817**	1.71248*	0.63047	1.52495	2.27196*
0.20	1.28042	3.09314***	3.25131***	2.35755**	1.22826	2.22379**	1.53979	1.41382	1.49852	2.63880***
0.25	1.43469	3.10212***	3.63794***	2.79296***	1.03682	2.06712**	2.22221**	1.61729	1.88445*	2.59469***
0.30	1.55772	3.68067***	4.19129***	3.12030***	1.33225	1.98722**	2.58199***	1.96882**	1.93857**	3.15938***
0.35	1.99937**	3.63969***	4.19047***	3.82780***	1.80477*	2.17775**	2.52118**	2.49695**	2.15861**	3.34265***
0.40	2.43783**	3.85793***	3.93124***	3.81003***	1.79322*	1.97880**	2.70424***	2.39967**	2.09620**	3.43690***
0.45	2.40610**	4.06462***	3.64787***	3.96401***	1.74282*	1.79993*	2.98762***	2.65935***	2.41827**	3.65302***
0.50	2.03738**	4.27068***	3.42881***	3.88798***	1.80548*	1.81587*	2.66923***	2.72463***	2.85514***	3.41732***
0.55	1.78503*	4.13698***	3.29239***	3.90609***	1.61049	1.78817*	2.74163***	2.40865**	2.43931**	3.21944***
0.60	1.71540*	3.87406***	2.64115***	3.92679***	1.89591*	1.78142*	2.67800***	2.20535**	2.44444**	3.76192***
0.65	1.67986*	3.60566***	2.22063**	3.70509***	1.59795	2.03906**	2.65161***	1.91404*	2.38240**	3.30562***
0.70	1.53965	3.03611***	2.23563**	3.81507***	1.89158*	1.86701*	1.85497*	1.61516	2.05502**	3.03386***
0.75	1.59481	2.42838**	2.21075**	3.45093***	1.50933	1.76310*	1.44339	1.39536	1.89053*	2.70552***
0.80	1.56691	2.04911**	1.91331*	3.31076***	1.32992	1.76922*	1.10208	1.21829	1.53703	2.87963***
0.85	1.19596	1.45309	2.13917**	2.60773***	1.77638*	1.52064	1.16519	1.09180	1.08585	2.33467**
0.90	1.12815	1.21249	1.63700	1.58095	1.47213	1.09164	1.14969	0.74984	0.88437	1.33077
0.95	0.71229	0.88209	0.62875	0.90546	1.44546	0.75744	0.75872	0.78207	0.75286	0.84527

Notes: τ represent quantiles; test statistic is tested at the 5%, where critical value = 1.96; [***], [**], and [*], are [1%], [5%], and [10%] respective significance levels for critical values of 2.567, 1.96, and 1.645.

respectively, and this relationship is largely bi-directional. The findings substantiate the choice to ascertain how the two assets are connected across different quantiles of both the dependent and independent variables.

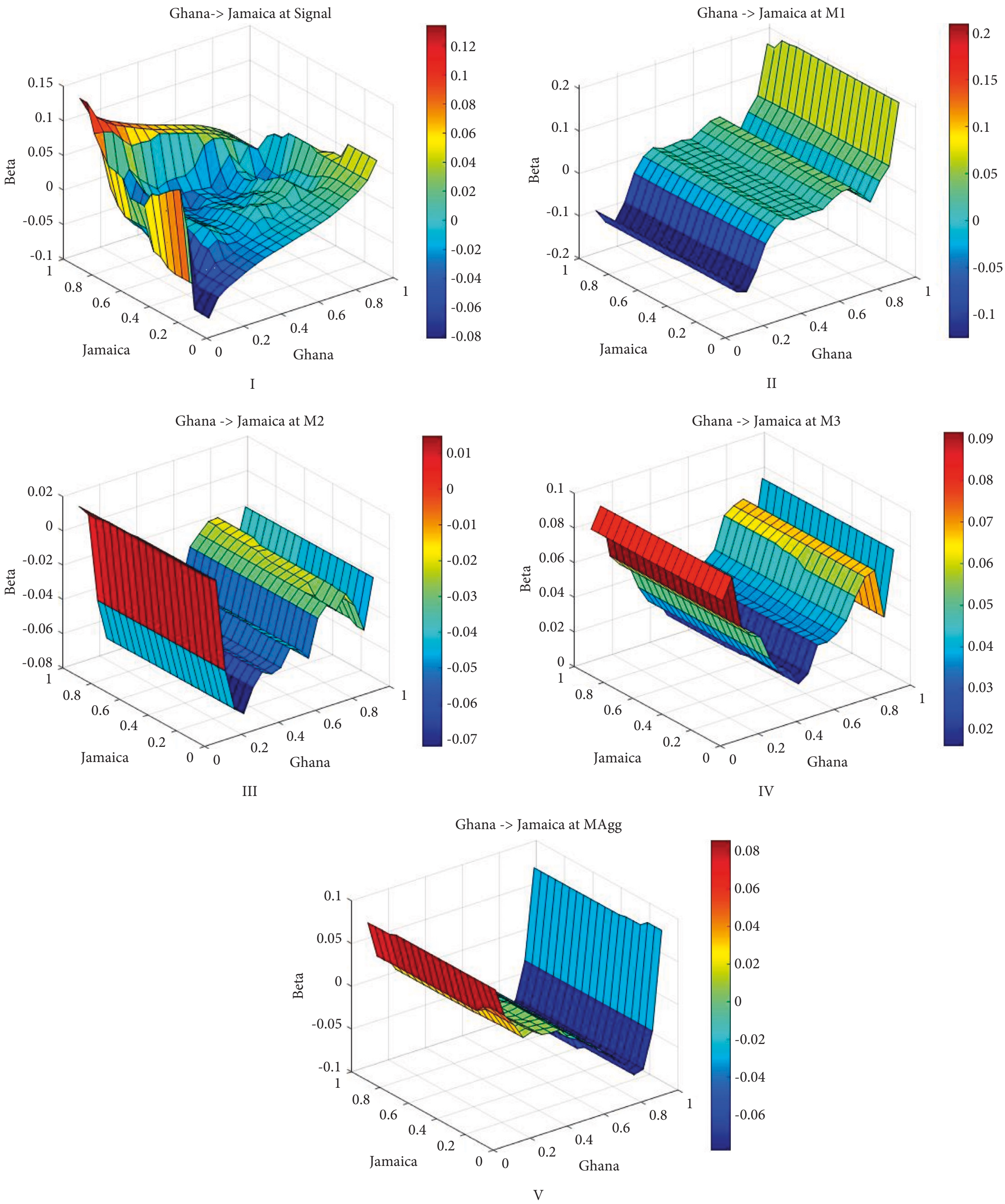
3.3. QQR Analysis. The results from the causality in quantiles give the impulse to probe further into the different conditions of the regressand and regressors to assess the conditional impact of GSECI returns on the various conditions of JSEIND returns. Based on the bi-directional causality established, this analysis is carried out for the reverse to assess the conditional impact of JSEIND returns on the various conditions of JSEIND returns. This is achieved by extending the analysis to the QQR framework. This section discusses the estimates generated from the QQR technique.

The slope coefficients (to reserve space, the numerical QR and QQR estimates for signal and decomposed series are available upon request) $\beta_1(\theta, \tau)$, which represents the effect of the π_{th} quantile of GSECI (JSEIND) returns on the θ_{th} quantile of JSEIND (GSECI) returns are plotted with three-dimensional (3D) graphs in Figure 4. Due to the nonparametric process involved in QQR estimations, it is not practical for the significance levels of the coefficients to be determined. Nonetheless, the QQR estimates are confirmed by the QR results, as detailed in the robustness analysis section. In the analysis of the 3D plots in Figure 4, high, medium, and low quantiles are used as a resemblance of bullish, average normal, and bearish market states, respectively. The quantile range 0.05~0.35 is designated as the bearish market state, 0.40~0.60 as the average market state, and 0.65~0.95 as the bullish market condition.

For the signal data, the relationship Ghana- > Jamaica results in mild negative coefficients across the lower and median quantiles of both GSECI returns and JSEIND returns. Across the upper quantiles of both markets, the relationship is positive. Thus, diversification and safe-haven benefits are available at stressed and average market conditions for any causal influence initiated by the Ghana stock market towards its Jamaican counterpart. On the reverse, when Jamaica causes Ghana, there tend to be mild positive relationships more than negative. However, this is close to zero and may not cause significant effects on any diversification prospects between the two markets.

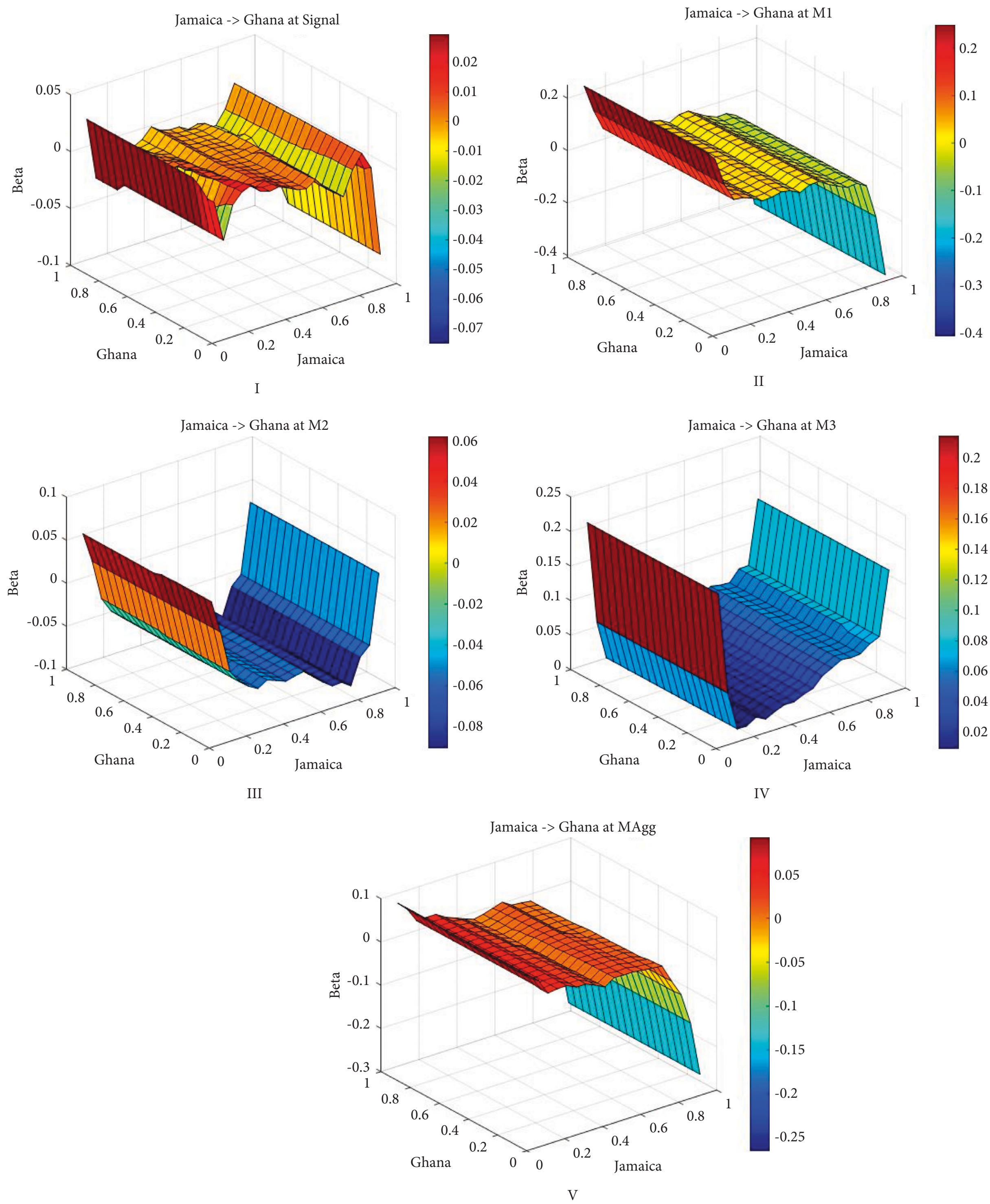
It should be noted that analysing the relationship between the two markets in a static paradigm (i.e., using the signal data) could result in biased conclusions since market responses are heterogeneous. Thus, following the fractal markets hypothesis, the VMD was used to delineate the signal data into modal functions that not only help to reveal short-, medium-, and long-term dynamics but also deal with nonstationary and noisy signals and reveal true linkages between the markets. Therefore, we analyse the relationships across the short- (M1), medium- (M2), and long-term (M3) trading periods as well as the residue (MAgg).

Unlike the relationships between the signal data, the modes reveal a clearer picture of the relationship between the GSECI and JSEIND market returns. From the short-term series (M1), the results indicate that when Ghana is causing Jamaica, GSECI and JSEIND are negatively (positively) related across the lower (higher) quantiles. However, the coefficient of the positive relationship is below 0.1. Conversely, when Jamaica causes Ghana, GSECI and JSEIND are positively related across lower quantiles but negatively related across higher quantiles of both markets.



(a)

Figure 4: Continued.



(b)

FIGURE 4: 3D plots of QQR estimates. (a) Ghana to Jamaica. (b) Jamaica to Ghana. Notes: this figure displays the QQR slope coefficients in 3-dimensional graphs. Z-axis shows the slope coefficients, Y-axis shows the quantiles for the regressand, and X-axis shows the quantiles for the regressor. The colour bar shows the colour associated with a coefficient in the 3D plane. (a) shows the 3D graphs for the relationship "Ghana- > Jamaica" and (b) shows the 3D graphs for the relationship "Jamaica- > Ghana."

From the medium-term series (M2), the market returns of the two exchanges are negatively related across all quantiles except for the quantile range 0.05–0.10, which reveals a negligible positive relationship. This holds for both Ghana- > Jamaica and Jamaica- > Ghana. However, from the long-term series (M3), the market returns of the two exchanges are mildly positively related across all quantiles. This holds for both Ghana- > Jamaica and Jamaica- > Ghana. From the residual series (MAgg), the market returns of the two exchanges are positively related across the quantile range of 0.05–0.50 but negatively related across the quantile range of 0.55–0.95 of both markets' returns. This also holds for both Ghana- > Jamaica and Jamaica- > Ghana. Thus, despite a few peculiarities, the relationships are generally comparable regardless of the causal or affected market.

The results confirm that the causal relationship between the stock market returns of Ghana (GSECI) and Jamaica (JSEIND) does not only vary across market conditions but investment horizons. This observation confirms that, indeed, market responses are asymmetric. In the context of portfolio management, negative relationships between the markets signal that diversification potentials exist. Baur and Lucey [29] define a hedge (safe-haven) as an asset with an inverse no correlation with another asset in an average (stressed) market state. Conversely, when, in an average market state, the correlation between an asset and another is positive but does not approach unity; then, the asset is a diversifier [29, 30]. Therefore, in the context of the study's findings, the negative relationships found across the lower quantiles (stressed market states) signal safe-haven benefits whereas those found across the median and upper quantiles (average and good market conditions) signal hedging benefits. The few mild (and negligible) positive relationships revealed across some quantiles suggest that returns from GSECI are JSEIND diversifiers for each other.

To verify the QQR results, the QR estimates are compared with those of QQR. This facilitates inference of the connections given by the QQR from those shown by the QR. The QQR estimates are the decomposed estimates of QR into particular quantiles of the regressors, and hence, the QQR estimations may be validated by comparing their coefficients to those of QR [31]. Figure 5 presents line graphs of QR and QQR coefficients to demonstrate this. The graphs visually represent the QR estimations to reveal the trend of increases and/or decreases in GSECI (JSEIND) returns and the accompanying movements in JSEIND (GSECI) returns. The plots also validate the QQR by comparing it to the QR estimates [14, 31]. The horizontal (vertical) axis of each graph presents the quantiles (QR/QQR estimates). Gold and blue lines correspond to QQR and QR estimates across quantiles.

From Figure 5's graphs, it could be noticed that the QR and QQR estimates confirm each other with slightly higher/lower QQR magnitudes across some quantiles. Nonetheless, the QRR estimates are validated by those of QR, as they generally have comparable directions.

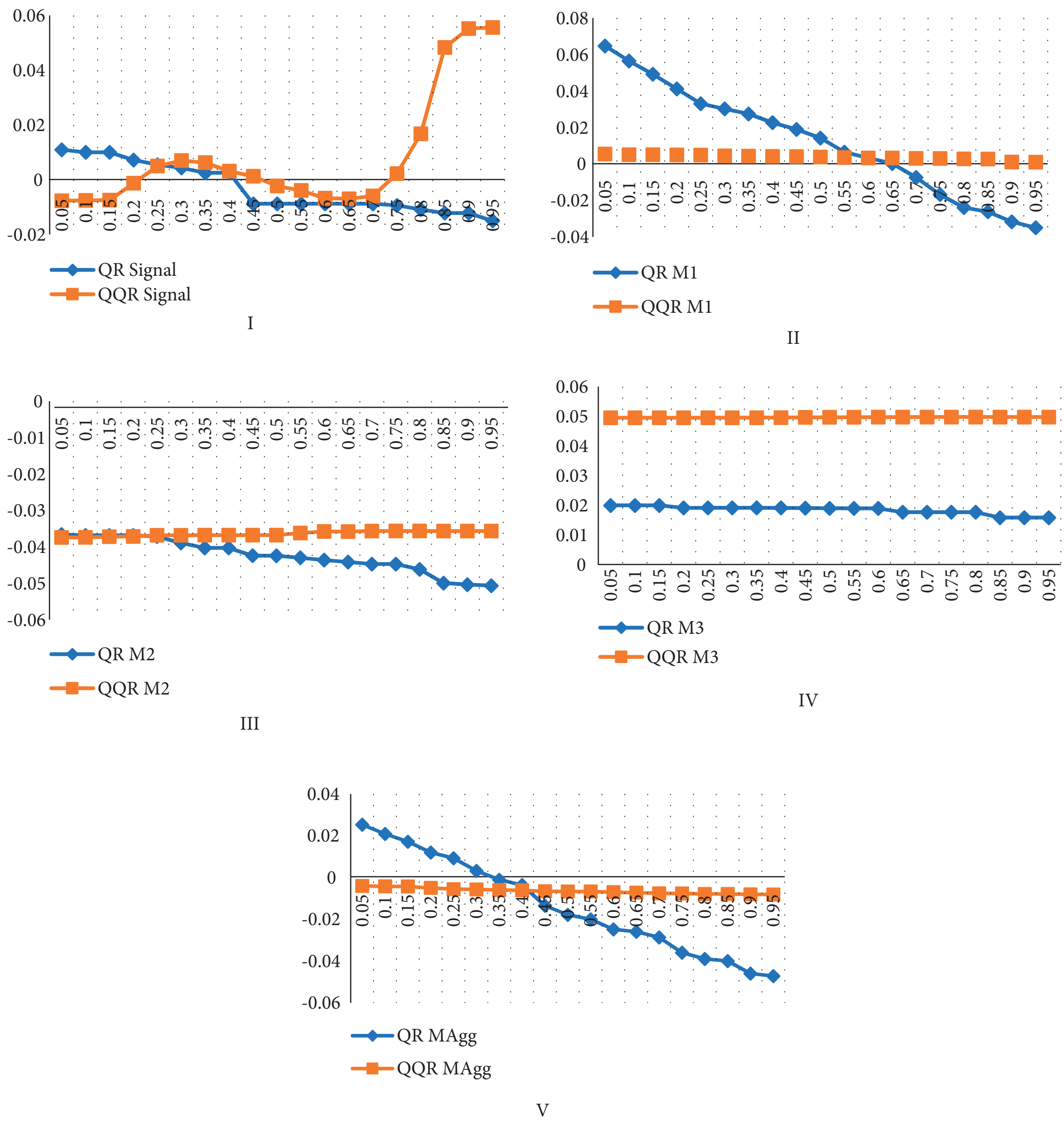
4. Implications of the Findings

The findings from the study have notable implications for market participants, policymakers, and regulators. The wavelet coherence analysis reveals that, at high (low) frequencies (scales), neither of the market returns from GSECI or JSEIND consistently drives the other. The interspersed positioning arrows underscore the power of transitory relationships across short-term scales (up to the quarterly trading scale). Impliedly, in as much as diversification may prevail in the short term, as further evidenced by the QQR analysis, market participants should be wary of fleeting market dynamics that could cause one variable to either lead or lag the other. When relied upon, market participants could be misled.

In the spirit of the fractal markets hypothesis, investor responses differ across investment horizons [9, 10], and when given any structural breaks in the market, investors tend to modify their trading patterns, and this results in the possible creation of new markets, as hypothesised by the adaptive markets hypothesis [11]. This partly explains the interspersed and inconsistent relationships between GSECI and JSEIND in the short term. Given the quest to satisfy overriding portfolio goals (maximising returns whilst minimising risks), investors would intensify their search in the short-term trading periods, particularly in crisis periods. As a corollary to his relentless search, cross-market/asset comovements are deepened, as argued by the proponents of the competitive markets hypothesis [32]. Hence, when paid attention to, the inconsistent positioning arrows that emerge in the short term are found to mostly correspond to crisis periods, for instance, the positioning arrows between 2012 and 2014 (the European debt crisis), 2016 (Brexit), 2020 (COVID-19 pandemic), and 2022 (Russian-Ukrainian conflict). During these periods, crises from top-advanced markets diffuse across emerging markets through financial market contagion (Agyei et al.) [4, 21]. Hence, it is natural to expect that, in similar crisis periods, several fleeting market dynamics may prevail. Investors and regulators must, hence, not pay heed to such dynamics but rather follow the fundamental (and historical) behaviour exhibited by the assets (markets) in question.

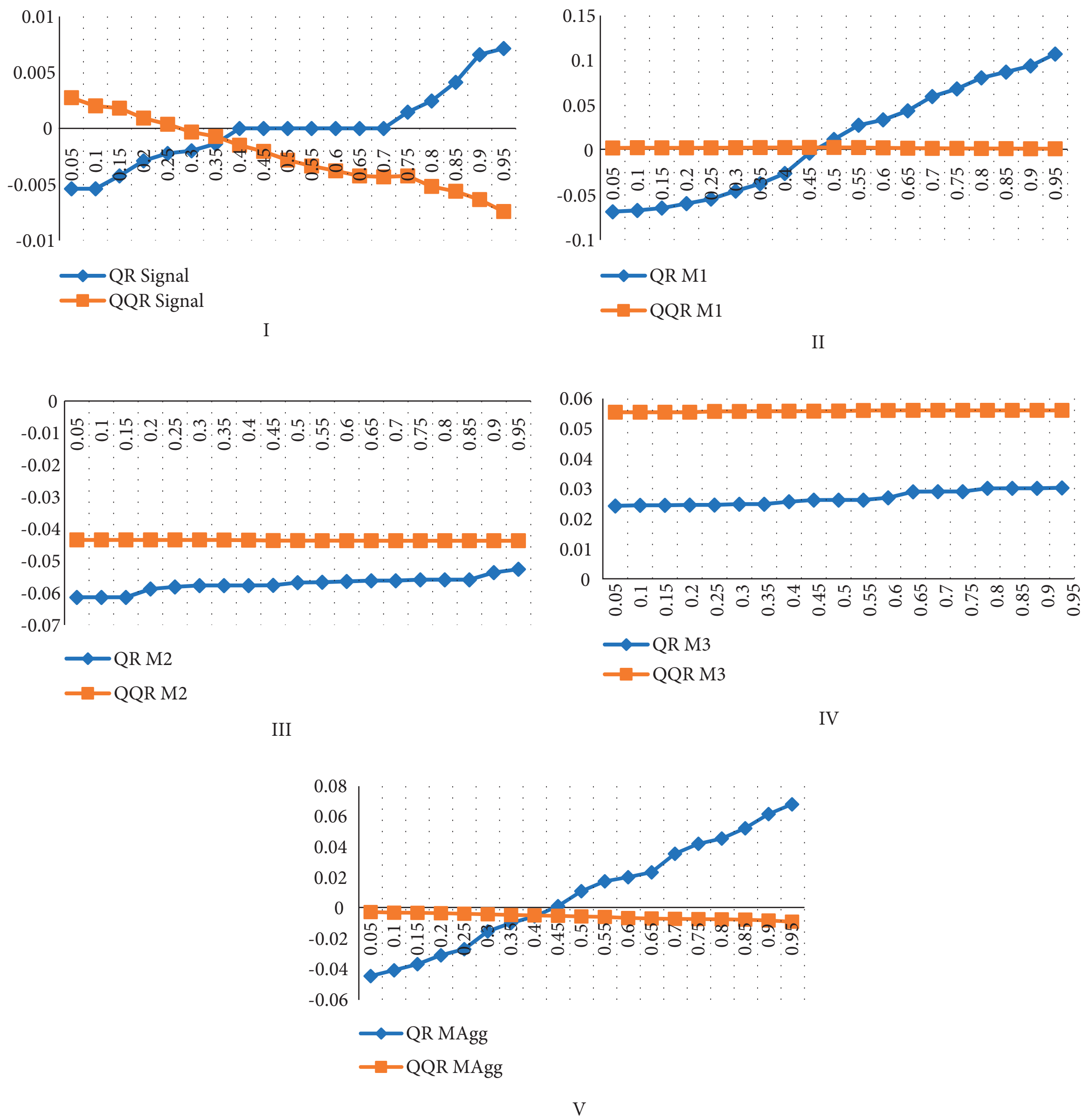
Furthermore, findings, from the QQR analysis, underscore essential diversification benefits between GSECI and JSEIND stocks. During turbulent trading periods in one market, either asset could be a safe haven for the other. Similarly, these assets tend to be a hedge for each other in normal trading periods. Impliedly, international investors could consider the inclusion of both GSECI and JSEIND stocks to achieve the diversification desired. Thus, the movement of capital between the Jamaican and Ghanaian markets may have no significant effects on portfolio management. Impliedly, as explained by the horizontal interdependence theory, the new partnership (MoU) between the stock markets of Ghana and Jamaica would facilitate the movement of funds between the two markets with more ease [33]. Therefore, investors could take advantage of the MoU to allocate investable funds between Ghanaian and Jamaican assets.

Findings from the study further imply that market participants should not only consider investment horizons when managing risks. The results indicate that market dynamics could change based on the condition or state of either market. Therefore, in addition to assessing the investment horizon, investors and policymakers should analyse the condition of the market. Stressed (bearish) periods



(a)

Figure 5: Continued.



(b)

FIGURE 5: Line graphs of QR and QQR estimates. (a) Ghana to Jamaica. (b) Jamaica to Ghana. Notes: this figure presents the line graphs of the QR and QQR estimates. Blue spots are QR estimates whereas gold spots are QQR slopes. The horizontal axis for each graph denotes the quantiles and the vertical axis displays the slope coefficient. (a) shows the line graphs for the relationship Ghana- > Jamaica and (b) shows the line graphs for the relationship Jamaica- > Ghana.

in both markets in the long term result in positive connectedness between the markets, whereas the average and bullish market states yield negative connectedness between the two markets. These relationships are not clearly portrayed in the static paradigm (i.e., from the signal data), so market participants should equally be concerned with the asymmetric relationships between assets from Ghana and Jamaica across the short-, medium-, and long-term trading periods.

Economically, given that the cone of influence from the coherence plot does not cover beyond the annual scale, co-movements between GSECI and JSEIND beyond a year may be less significant for policy management. Hence, long-term economic projects between the two economies may have to be demarcated into medium-term components, and their progress monitored annually or biennially. The significant diversification prospects between the two markets signal that the two stock markets could facilitate the inflow of capital assets for extended growth and development of their overall economies.

Finally, the relationships found between GSECI and JSEIND could further stimulate policy actions to attractively regulate the two stock markets. Given the safe-haven and hedging benefits available to these markets, a potent stock market is critical to attracting more capital flows to the economies of Ghana and Jamaica. Between the two countries, the results indicate that the Ghanaian market has significant potential to drive changes in the Jamaican market. Therefore, when aligning policy interests, it would be prudent for policymakers in Ghana to always lead or advance significant areas for collaboration. As identified from the preliminary analysis, the Jamaican market has a higher market capitalisation relative to its Ghanaian counterpart. In this regard, proposals for collaborations from Ghana could be a significant strategy for the GSE to tap into the resources of the JSE and gradually build up its capitalisation to match that of JSEIND. It should be noted that when policies are rather initiated by Jamaica, and Ghana stand the chance of lagging given its less capitalisation and relatively less resource base. This may, in turn, delay the achievement of the objectives of joint policies whilst rendering the partnership ineffective.

5. Conclusions

The newly signed partnership agreement between the Stock Exchanges of Ghana and Jamaica raises concerns over possible implications for portfolio management and attraction of capital flows to the respective economies. This study examined the co-movement dynamics between stock market returns from Ghana and Jamaica with daily data from 04 April 2011 to 17 March 2022. In addition to the wavelet coherence analysis, the causality in quantiles and quantile-on-quantile regression (QQR) analysis with decomposed return series using the variational mode decomposition (VMD) approach were carried out. The empirical analysis was targeted at responding to questioning themes like (i) the fundamental relationship between GSE and JSE, (ii) whether the stock market returns from GSE comove with their JSE counterparts, (iii) whether the comovement between GSE and JSE differ across investment horizons, and (iv) the relationship between stock returns from GSE and JSE across the bullish, average, and normal market conditions.

The findings from the bi-wavelet analysis divulged a fundamentally low connectedness between stock returns from Ghana and Jamaica. The co-movement between the returns from the two markets was spotted consistently during long-term trading horizons of crisis periods. Significant bi-directional causal relationships were found between stock returns from Ghana and their Jamaican counterparts across the short-, medium-, and long-term periods. Findings from the QQR analysis underscored asymmetries but further divulged safe-haven, and hedging advantages during bearish and normal trading periods across different trading horizons.

The findings underscore significant diversification advantages for portfolio management. Following the implications of the findings, market participants should be wary of fleeting market dynamics that could cause one variable to either lead or lag the other because, when relied upon, market participants could be misled. Investors and regulators must, hence, not pay heed to such dynamics but rather follow the fundamental (and historical) behaviour exhibited by the assets (markets) in question. Investors could take advantage of the MoU to allocate investable funds between Ghanaian and Jamaican assets after analysing market conditions (bullish, bearish, and normal). Policymakers and regulators could attract international investors and promote the flow of funds between the two economies through effective regulation of stock markets. Given that the cone of influence from the coherence plot does not cover beyond the annual scale, co-movements between GSECI and JSEIND beyond a year may be less significant for portfolio management. Hence, long-term plans between the two markets may have to be demarcated into medium-term components and their progress monitored annually or biennially.

Future works could investigate the hedge effectiveness between combined stocks from Ghana and Jamaica. It would be prudent to examine the optimal proportions of each asset that could be maintained in international portfolios. Similarly, together with these assets, world risk sentiment (see [5, 15]; etc.) could be incorporated into a multivariate setting, as used by [2], to additionally test the hedging prospects of these assets [34–37].

Data Availability

The data used in the study are under license with EquityRT.

Conflicts of Interest

The author has declared that he has no conflicts of interest.

Acknowledgments

The researcher is grateful to Mr. Ahmed Bossman for estimation assistance.

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