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Co-movement between equity index and exchange rate: Fresh evidence from COVID-19 era

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\begin{abstract}
This paper probes deeper into the co-movement of Ghana’s equity index and exchange rate with international equity markets and further determine whether these co-movements are driven by global uncertainties. Also, we sought to determine how the COVID-19 pandemic alters the dynamics of these relationships. We employ the wavelet technique to data from January 19, 2012 to March 1, 2021 to the split between pre-COVID-19 and COVID-19 periods. The results reveal that the dynamics of co-movement or interconnectedness of exchange rate and Ghana Stock Exchange composite index has evolved over time and across frequencies. Besides, the cone of influence, as shown by the wavelet spectrum, does not cover the entire data frequency which suggests that long-term forecast of exchange rate and equity index in Ghana beyond four years could be misleading since significant levels of interdependences are concentrated around the mid-team scales. In addition, we found evidence to support low-medium term lead-lag connections between exchange rate and Ghana Stock Exchange Composite Index in 2013 to 2014 and 2016. Further, the co-movement between exchange rate or Ghana Stock Exchange Composite Index and international equity markets show similarly weak association at all scales. A closer scan of the interdependencies among these variables are more intense during COVID-19 than during the pre-COVID-19 period. Finally, we observe a strong co-movement between the rise in COVID-19 cases and exchange rate at higher frequency scales where exchange rate lags Ghana’s equity index and they are out-of-phase.

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\end{abstract}

\textbf{Introduction}

The novel coronavirus (COVID-19) pandemic has in its short existence caused an economic downturn and affected financial markets worldwide. The continuous spread of the virus has unleashed devastating effects resulting in capital market uncertainties, oil price slump and partial or complete lockdown of economic activities. For instance, according to Baker, Bloom, Davis and Terry [10], the global equity markets have seen unusual jumps which are attributed to the threat and

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US protocol restrictions on the COVID-19 outbreak. Similarly, two months after the virus was recorded in Wuhan, China, oil price dropped significantly by around 30% which is the largest slump in decades [81]. The cost and the unprecedented effect of the novel coronavirus raises questions on market behavior under such global crisis.

The discussions, so far, on the various financial media and in some recent studies [40] compare the economic effect of COVID-19 and the 2008–2009 Global Financial Crisis (GFC), which started in the United States. Over the past decades, issues on the GFC have received considerable attention concerning market interconnectedness, spillover, and contagion effects in the literature. Empirical studies on the subject suggest that there are variations in the results of co-movements of capital markets during financial and non-financial crises [57]. This suggests that transmission mechanisms could be crisis contingent on deviations in market phenomena. However, the COVID-19 crisis, in its unique form, scope and time, was recorded in most countries around the same time. For instance, the closest health epidemic to COVID-19 is the Severe Acute Respiratory (SARs) for which China and Hong Kong were the most prevalent risk areas. But the COVID-19 is global which has the potential to trigger a long term shifts in the cost of equity [36]. The sudden spread of the virus and subsequent lockdown of most countries has given investors and corporate institutions little time to re-position their investment portfolios. Thus, the COVID-19 pandemic could engender different type of spillovers and contagion compared to other financial crisis.

The Federal reserve policy actions and US stock markets generally, plays a central role in influencing emerging market stock market movements [39]. The growth evolution of REITs is accompanied by a natural inheritance of some of the characteristics of stock movements, such as regional and global interdependence [18,47,49]. Conventional and unconventional responses from US economic and policy development and quantitative easing to financial crises have had collective spillover impact on REITs of emerging markets economies. Gupta and Marfatia [38] find that the explosion of large scale asset purchasing programme by the US Federal Reserve led to abundant global spillovers to a number of emerging economies foreign exchange markets. Marfatia et al. [53] also show that US economic and policy development news have time-varying impacts on global REITs returns through the stock market capitalisation to GDP ratio of the respective market, according to Marfatia et al. [53]. These point out that both economic and policy uncertainties and the information associated with them impact on global REITs in a similar way they affect stock returns. This leads to the cause to establish the closeness between foreign exchange and stock markets using a methodology that captures the unstable market dynamics and external instabilities.

The extant literature on the interdependence amongst exchange rate and equity markets are well developed but are more diverse and there is no consensus. Earlier, some studies investigated the short-run and long-run co-movements between exchange rate and stock market returns using linear time-series models. Adjasi and Biekpe [1], for instance, explored the relationship between stock markets returns and exchange rate co-movements in seven African countries. Their results show that in the short-run, exchange rate depreciation reduces stock returns while in the long-run, exchange rate depreciation leads to increases in stock market prices in some countries. In a similar study, Adjasi et al. [2], found that there is a negative relationship between exchange rate volatility and stock market returns in the long-run.

Moore and Wang [58] examine the dynamic linkages between stock returns and exchange rate volatility and find that stock prices have a reverse directional response to a fall in a countries local currency level. The authors argue that the depreciation in the local currency boosts the attractiveness of domestic companies by increasing their international trades, which results in greater international inflow to the domestic market. Stock markets ultimately, will respond to the increase in cash flow, causing the price to rise. This finding is consistent with other studies such as Zhao [86], Adjasi et al. [3], Boako et al. [16]. Some studies could not find any significant link between the two variables.

The varying results and lack of consensus can be attributed to many factors: key among them is the methodological inadequacy. While Bahmani-Oskooee and Saha [8] posit that low power of conventional tests is the main cause for the lack of co-movement, Dahir et al. [22] claimed the time series models employed in the literature fail to take into consideration the time and multi-scales dimensions but are restricted to only short and long run terms. In response to this criticism, some research have adopted more complex methods such as Markov switching, nonlinear ARDL and Copulas [8,82]. Majority of these studies do not consider some important characteristics of time-series data such as nonlinearities and structural breaks. In the face of high volatilities and turbulence during period of crises, such as COVID-19, limiting modeling to conventional methods is problematic.

In resolving these methodological drawbacks (which is the main source of conflicting results) in the literature, the wavelet coherence technique we have adopted proves to yield consistent results. This stems from its superior properties of using the time-scale framework. Our results corroborate He et al. [41], Yang et al. [84] and Dewandaru et al. [25] in the use of time-scale framework. They opine that in order to obtain dependable results in co-movement and/or contagion analysis, it is better to simultaneously assess the relationship between variables at different frequencies and times [79]. Also, by its multi-scale decomposition of time series, the wavelets technique offers a valuable means of exploring the complex dynamics of financial time series [11]. The decomposition captures both time series and domain simultaneously, thus enabling higher and lower frequencies to be distinguished. This is important for deciphering fine co-movements and possible contagion because, the markets comprise of traders who operate on different time horizons (i.e. daily, weekly, monthly, etc.) which corresponds to short-, medium, and long-term periods [6]. We specifically employ the bivariate wavelet coherence, multivariant and the partial wavelet analysis.

Besides, the emerging trend of the effect of COVID-19 pandemic on various economic indications are centered on advanced markets with little or no attention to promising markets like Ghana. Even the very few studies that have so far examined COVID-19 and economic issues in Africa focus on wide subject areas. The question is how emerging markets, such
as the Ghanaian financial market, have reacted to the pandemic since the first case was confirmed. Assessing the impact of the pandemic on emerging stock markets, Topcu and Gulal [71], reveal that, the pandemic has negatively affected stock markets of emerging economies. However, the market dynamics involving specific indicators and how they relate to other international assets during the pandemic is unknown.

In periods of economic uncertainties, investors consider other alternate markets, especially emerging markets, to diversify their equity portfolio or as a safe haven [36]. The literature, on emerging market, documents a weak co-movement between local market to that of their international equivalents [7,13,14]. Yet not much is known of the influences of the COVID-19 pandemic on the correlations with the financial markets. There is, therefore, the need to re-examine the dynamics of co-movement of capital markets and its spillover effects from emerging market perspective in light of the COVID-19 pandemic.

In this study, we concentrate on Ghana for two main reasons. First, developing markets, like Ghana, have attracted international investors who are seeking low cost of funding and risk diversification due to the adoption of innovative financial products and massive structural reforms in recent years [14]. As a result, Ghana’s foreign exchange and equity markets have experienced significant restructure and integrated into the global markets resulting in rapid growth in the financial market and increase liquidity. In times of uncertainties, especially on major international markets, investors consider alternative markets, such as developing or emerging markets (see [36]), as a safe haven for their investments. Knowing the link between exchange rate and equity index, in Ghana, as well as how they co-move with their international counterparts will influence investment direction, strategic policy development and reshaping further research under such crisis. Second, in recent years, large amount of foreign capital flow to Ghana has helped to finance high debt obligations and also caused the financial market to become vulnerable to external conditions and increase market volatilities. The covid turbulence could affect the relationship between foreign exchange and equity returns. It is important to re-examine this relationship under COVID-19 to ascertain if there is/are difference(s). Specifically, the paper seeks to (a) examine whether the rise of COVID-19 cases affects the exchange rate and equity market volatility, (b) explore the link between the exchange rates and Ghana’s equity market during COVID-19 period, (c) examine the co-movement between Ghana’s and the international equity market.

This paper makes numerous contributions to the existing literature concerning the impact of COVID-19 on the financial markets. Firstly, it provides a theoretical basis for examining the dynamic relationship between foreign exchange/local equity index and global equity markets. This provides the foundation to engender further studies on this nature which have been very limited hitherto. Secondly, the results of the study offer new insights into the diversification potential of Ghana’s foreign exchange rate and equity returns to both local and international investors. The study answers the question as to whether or not the inclusion of Ghana’s equity or currency exchange in a portfolio of global assets proffers diversification benefit to investors, especially during periods of market turbulence. Thirdly, the use of bivariate, multivariate and partial wavelets techniques brings to light the specific dynamics between foreign exchange and equity markets. Unlike the multiple wavelet correlations which provide only one indication of a leading variable in a system at a given scale, the bivariate and partial wavelets offer many pointers of leading/lagging variables at different scales across the sample period and also controlling for specific conditions. The outcome of this analysis is a fine-tuned relationship between two markets which can be replicated at minimal discrepancies. Lastly, our study does not only provide insight for investment, but it also provokes policy responses targeted at safeguarding the young foreign exchange and equity markets against unwholesome foreign investments as well as contagion effects. Specifically, our study makes it possible for policy actions to be time and frequency oriented to yield the needed results.

The paper is structured into four sections. The second Section looks at detailed methodology while the third Section is focused on results and discussion and finally the Section four presents the summary and conclusion of the work.

Materials and methods

Bivariate wavelet coherence

The literature on the short- and long-term relationship or co-movements between market variables in Africa has been well documented using various econometric models. Predominant among them are cointegration analysis, ARCH and GARCH and different forms of regression models [66]. In line with modern econometric models for analyzing variable nexus or inter dependences, we employ the wavelet estimation technique. Although this technique is new, it has not been used extensively in this area of finance. The wavelet approach is most appropriate for our analysis because of its ability to offer better trade-off between detecting discontinuity and oscillations in the time series data. Wavelet analysis considers the behavior of the data in time and frequency domains, compares to other models that concentrate on only time. It has the capability to analyze variables on different frequencies to explore the details of joint movements across various time horizons without distorting information [13].

The strength and robustness of the wavelet methodology is seen through the various pros over other econometric models in detecting market linkages. Also, according to Fitti et al. [31], the frequency-based component allows for detailed understanding of the interlinkages based on the fundamentals exhibited in the data. In addition, the same authors explain that, the wavelet approach requires no pre-treatment of the data series and it easily decomposes the data into various time-frequency components which guides against any abnormalities in the data structure and loss of salient information. More so, the technique provides graphical tools that aid in examining heterogeneous market properties and gives details to whether
the market exhibits short-, medium-, or long-term interlinkages. These help to differentiate between investors who operate on short-to-long term spectrum on the market. Hence, wavelet application to dynamics in prices in relation to the rise in COVID-19 cases could provide fresh information on market behavior across these different asset classes.

Wavelet, by definition, is a small wave which can stretched over time to expose frequency components from complex signals. The wavelet function has a null mean which is localized in time and frequency. If the factor $1/\sqrt{q}$ is the normalization component that ensures unity in variance, $t$, $q$ and $\tau$ are the time scale and time position parameters, respectively, then the mother wavelet function (wavelet transform) can be expressed as

$$
\Phi_{\tau, q}(t) = \frac{1}{\sqrt{q}} \Phi \left( \frac{t - \tau}{q} \right)
$$

(7)

There are different types of wavelets as used in finance research. One of them is the daughter of the mother wavelet which is suitable for our analysis called the Morlet Wavelet. The type is most preferred due to its ability to exhibit high characteristics of localization in frequency and time domain found within the Gaussian fold. The Morlet wavelet can be expressed as

$$
\Phi_0(\gamma) = \frac{1}{\sqrt{\pi}} e^{i\eta \omega_0} \frac{1}{\sqrt{e^{2\gamma^2}}}
$$

(8)

where the negative fourth root is a normalization term, $\eta = t/q$ and $\omega_0$ are the time and dimensionless central frequency parameters. Rua and Nunes [79] recommends setting $\omega_0$ to 6, since this value produces the best time-frequency localization.

Wavelet analysis requires either a discrete or continuous transformation. The appropriate transformation required for our set of data $\{x(t), 1, \ldots, n\}$, which is continuous in nature will be the Continuous Wavelet Transform (CWT). The aim of the transformation is to preserve the energy of the data series and use it later to investigate the power spectrum. With regards to $\Phi(t)$, the resultant function of the CWT can be written as

$$
V_{\tau, q}(t) = \frac{1}{\sqrt{q}} \int_{-\infty}^{\infty} x(t) \Phi^* \left( \frac{t - \tau}{q} \right) dt
$$

(9)

where $*$ is a complex conjugate. From the above, the variance of the process is expressed as

$$
||x||^2 = \frac{1}{c_\Phi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} [V_{\tau, q}(t)]^2 dt \frac{dq}{q^2}
$$

(10)

If $V_{\tau, q}(t)$ is the CWT of the signal $\{x(t), 1, \ldots, n\}$, then $|V_{x}|^2$ is called the Wavelet Power Spectrum which represents the energy density of the signal in the frequency-time domain.

For two different continuous wavelets transform ($V_x$ and $V_y$), the best tools to detect and quantify the nexus between these variables using wavelet are the Cross-wavelet power (CWP), wavelet phase-difference (WPD) and wavelet coherence (WC). For the signals $x(.)$ and $y(.)$, the CWP (as seen in [43]), which shows the local covariance of the two signals at different scale and frequency, can be expressed as

$$
V_{xy} = |V_x V_y|
$$

(11)

The CWP, which is a correlation measure, uses the cross-wavelet coherence that provides a better insight to time varying relationship for a pair of bivariate data series (see [13]).

Similar to the Fourier coherency transformation, wavelets theory also uses the wavelet coherency which needs smoothing of both the cross-wavelet spectrum and localizing the individual the wavelet power spectra. The bivariate wavelet coherence, in line with Torrence and Webster [72] can be express as

$$
R_i^2 = \frac{|S(V_i^{xy})(s)|^2}{S(s^{-1}|V_i^x(s)|^2) \cdot S(s^{-1}|V_i^y(s)|^2)}
$$

(12)

where $S$ depicts the smoothing operator. A wavelet coherency could be considered as a localized correlation in the time-frequency domain. Like the traditional correlation measure, a wavelet coherency close to 1 illustrates a stronger similarity between the two variables while a measure of zero (0) shows no relationship [13,17]. Further, the WC is computed as the modulus of wavelet cross spectrum standardised to each individual wavelet spectra. This is essential in that it highlights the frequency and time interval where two signals have strong connections. It can be interpreted as the correlation between the two signals in time-frequency space. The statistical significance of the WC at 5% is shown as think black contour in the cone of influence.

The wavelet phase difference (WPD) function, according to Madaleno and Pinho [51], depicts lead/lag connections between any given two signals, which can be expressed as

$$
\theta_{xy} = \tan^{-1} \left( \frac{I(V_t^{xy})}{R(V_t^{xy})} \right), \quad \theta_{xy} \in [-\pi, \pi]
$$

(13)
To determine the phase characteristics of the series, the absolute value of \(\theta_{xy}\) is used. If the value is less than \(\pi/2\), then the series move in phase but if it is larger than \(\pi/2\), then the series are out of phase (anti-phase). Besides, the sign of the phase indicates which of the signals is leading the other [74,75]. In other words, the phase information is a local measure of phase delay between two signals as function of both frequency and time and is coded using arrow orientations to shown the relative phasing (lead/lag relationships) of the two signals. For instance, arrows pointing right (left) means the two signals are in phase (thus, anti-phase). If the arrows point right and up, means the second variable is lagging while Right and down shows the second variable is leading. Alternatively, if arrows point left and up it means the second variable is leading and a left down shows that the second variable is lagging. The phase information are indicated on the graphical region characterised by high coherence and phase difference. The CWT, as discussed above, has some challenges. First, the \(V_x (q, \tau)\) is a function of two parameters and, therefore, contains unnecessary information. Besides, it is numerically involving to analyze a time serious data using all the wavelet coefficients (see [34]). In spite of these challenges, it is widely used for finance research because it provides valuable apparatus for exploring how different periodic components of a signal changes over time, either individually or jointly.

Partial wavelet coherence (PWC)

We used both the Zivot and Andrews [87] unit root test and Narayan and Popp [59] structural breaks test. Both show structural break points that do not coincide with the COVID-19 pandemic. Hence, we conduct a partial wavelet analysis by controlling for COVID-19 infections in the co-movement between the variables. The difference in the wavelet coherence (pre-COVID-19 co-movements) and the partial wavelet coherence (COVID-19 period where we have mediate the coherence with COVID-19 infections) show the impact of the pandemic. In this case, we have directly involved the pandemic in the analysis other than just splitting the data into two.

By analogy, the PWC works in the same way the partial correlation where the effect of a third variable \(z(t)\) is suppressed for the relationship between two variables \(x(t)\) and \(y(t)\). In this case, COVID-19 cases, \(z(t)\) is controlled for in the relationship between the selected indices. This is achieved with the application of partial wavelet coherence [83]. In line with Ng and Chan (2012) and Wu et al. [83], the PWC is defined as

\[
R^2_p(x, y, z) = \frac{(R(x, y) - R(x, z) \cdot R(y, z))^2}{[1 - R(x, z)]^2[1 - R(y, z)]^2}
\]

where \(0 \leq R^2_p(x, y, z) \leq 1\) and follows the interpretation for \(R^2(x, y)\). If there is no difference between \(R^2_p\) and \(R^2\), then both \(y\) and \(z\) significantly influence \(x\).

Multivariate wavelets

For the purposes of robustness and to exemplify the usefulness of the multivariate wavelet technique in this study, we implement wavelet multiple correlation (WMCC) and wavelet multiple cross-correlation (WMCC) frameworks as seen in Polanco-Martínez and Abadie [69] and Fernández-Macho [30] and Ijasan et al. [44]. The WMCC and WMCC relies on the maximal overlap discrete wavelet transform (MODWT) to transform a signal into multiple wavelet and scaling coefficients. Compared to the discrete wavelet transform (DWT), the MODWT is purposed to possess a number of merits (see, [20,68]; etc.). For example, MODWT may be properly defined for arbitrary signal length, while DWT is limited to a signal that is dyadic (i.e. has a length with an integer multiple of a power of two). Practically, when used in the WMCC and WMCC, we are able to compare a large number of time series variables at once is single plots. In the same plots, we are able to determine the leading and lagging variables at the various scales, instead to several number of pairwise comparison. These features provide both simplicity and accuracy of analysis and inferencing.

The MODWT is described in Quilly & Adamowski [70]. From that the WMCC and WMCC can be determined. Given a real-valued random variable \(x_1 = x_{11}, x_{12}, \ldots, x_{1n}\), let \(W_{jk} = w_{j1k}, w_{j2k}, \ldots, w_{jnk}\) denote corresponding scale \(j, k\) wavelet coefficients obtained by applying the MODWT [35,68]. Let \(LA(\rho)\) denote a MODWT with a Daubechies least asymmetric (LA) wavelet filter of length \(\rho\) [23,35]. The WMCC may be defined as

\[
\Phi X(\lambda_j) = \sqrt{1 - \frac{1}{\text{max} \text{diag}(P_j)}},
\]

where \(P_j\) is the \((nxn)\) correlation matrix of \(W_{jk}\) and \(\text{max} \text{diag}(.)\) selects the maximum element in the diagonal argument. Given fitted values of \(z_i, \hat{z}_i, \text{WMCC}\) can further be written as

\[
\Phi X(\lambda_j) = \frac{\text{Corr}(w_{j1k}, \hat{w}_{j1k}) \text{Corr}(w_{j2k}, \hat{w}_{j2k})}{\sqrt{\text{Var}(w_{j1k}) \text{Var}(\hat{w}_{j1k})}},
\]

\[
\Phi X(\lambda_j) = \frac{\text{Corr}(\bar{w}_{j1k}, \bar{w}_{j1k}) \text{Corr}(\bar{w}_{j2k}, \bar{w}_{j2k})}{\sqrt{\text{Var}(\bar{w}_{j1k}) \text{Var}(\bar{w}_{j1k})}},
\]

\[
\Phi X(\lambda_j) = \frac{\text{Corr}(w_{j1k}, \hat{w}_{j1k}) \text{Corr}(w_{j2k}, \hat{w}_{j2k})}{\sqrt{\text{Var}(w_{j1k}) \text{Var}(\hat{w}_{j1k})}},
\]

\[
\Phi X(\lambda_j) = \frac{\text{Corr}(\bar{w}_{j1k}, \bar{w}_{j1k}) \text{Corr}(\bar{w}_{j2k}, \bar{w}_{j2k})}{\sqrt{\text{Var}(\bar{w}_{j1k}) \text{Var}(\bar{w}_{j1k})}},
\]

\[
\Phi X(\lambda_j) = \frac{\text{Corr}(w_{j1k}, \hat{w}_{j1k}) \text{Corr}(w_{j2k}, \hat{w}_{j2k})}{\sqrt{\text{Var}(w_{j1k}) \text{Var}(\hat{w}_{j1k})}},
\]
where \( w_{ij} \) is selected to maximise \( \Phi X(\lambda_j) \) and \( \tilde{w}_{ij} \) are the fitted values in the regression of \( w_{ij} \) on the rest of the wavelet coefficients at scale \( \lambda_j \) (i.e. wavelet multiple correlation).

The WMCC, on the other hand, can be generated by allowing a lag \( \tau \) between observed and fitted values of the variable at each scale \( \lambda_j \).

\[
\Phi X(\lambda_j) = \text{Corr}(w_{ij} \mid w_{ij} \tilde{w}_{ij, \lambda_j+\tau}) = \frac{\text{Cov}(w_{ij}, \tilde{w}_{ij, \lambda_j+\tau})}{\sqrt{\text{Var}(w_{ij}) \text{Var}(\tilde{w}_{ij, \lambda_j+\tau})}}.
\]  

(17)

The properties of a consistent estimator \( \Phi X(\lambda_j) \) are explained in Fernández-Macho [30]. Confidence interval (CI) of WMCC are obtained using Fisher (1915)'s transformation. The Fisher (1915)'s transformation is well-known for normalising and variance-stabilising for non-Gaussian sample correlation. For further reading on DWT, MODWT, WMC, and WMCC are extensively described in the literature (see [21,30,34,45,67] etc.).

Thus, the WMC provides a single correlation value to understand the relationship in the system of chosen variables at different frequencies. Further, the WMCC indicates the leading or the lagging index/variable in the system at different lags. In simple terms, WMCC indicate the maximum coefficient of determination in the linear combination of all variables at the various frequencies. Positive lags indicate lagging variables whereas negative lags represent leading variables [73].

**Data and preliminary analysis**

This study uses daily data of COVID-19 infection cases (referred to as COVID-19), Ghanaian cedi to the US dollar exchange rate (EXC), the Ghana Stock Exchange Composite Index (GSEI), S&P500 Index (SP500), and FTSE EPRA NAREIT Developed Index (DVLI). The series span January 19, 2011 to March 19, 2020. However, to provide a better insight to co-movement among our selected variables, we split the data into pre-COVID-19 period (January 19, 2011 to March 1, 2020 and COVID-19 period (March 2, 2020 to March 19, 2021). We start our COVID-19 data from March 12, 2020 because that was the date COVID-19 was first diagnosed and announced in Ghana while March 19, 2021 is the latest of week data available at the time of writing this paper. The price level data of GSEI, SP500, DVLI, and the EXC are all dollar denominated for the sake of uniformity. We chose SP500 in our analysis due to the relatively large-size of the market globally and that the United States remains one of the epicentres of the COVID-19 outbreak. Besides, we use FTSE EPRA NAREIT Developed Index because it is a fair equity index for developed Europe market. The datasets are sourced from the Datastream database in US dollar denominations, however, after cleaning and synchronizing the timestamps, we had in total 2438 realizations. This work uses the log-returns of all the data series which can be computed as \( r_t = \ln(R_t) - \ln(R_{t-1}) \) where \( R_t \) is the stock return at time \( t \).

**Graphical illustration of series**

Fig. 1 show the plot of exchange rate, the GSEI series over time and COVID-19 cases. We present only these two series because, in line with our objectives, we seek to determine the link between these variables and some international indicators. The EXC shows an upward trend both in COVID-19 and out of COVID-19 periods. On the other hand, the GSEI has seen a downward trend since May 2018. Also, the plot of COVID cases shows a rise, most especially after January 2021. This exponential rise could possibly be attributed to disregard to COVID-19 protocol during the December 2020 political campaign and elections. Besides, Fig. 2 shows the log-return of the series over the entire period (COVID-19 and pre-COVID-19). From the exchange rate plot, the series show stationarity with high volatilities between 2014 to 2016, which is similar to that of the GSEI series.

**Descriptive statistics**

Tables 1 and 2 show the descriptive statistics and correlation for the daily percentage log-changes of the data points. Table 1 specifically provides a brief overview of the price descriptive of the variables for COVID-19 and non-COVID-19 periods. From the table, it could be observed that the average exchange rate is higher during COVID–19 (5.7 Ghs/$) with a lower volatility (0.07) which is similar to that of S&P 500. Also, exchange rate is generally left-skewed with highly degree of skewness during COVID–19. The prices of foreign equity markets moved from right-skewness in non-COVID-19 to left-skew during COVID-19.

In Table 1, we provide the summary statistics of the log-returns of all series. We see that, except for GSEI (full sample) and GSEI (COVID-19 period), all the series exhibit positive average returns with varying magnitudes. Largely, the series are heavy-tailed and leptokurtic as indicated by their excess kurtosis values for both samples. There is a mix of left and right skewness varying between the series in the different sample. The Shapiro-Wilk test rejects the null hypothesis of normality at all convolutional levels of significance. All these point to asymmetry and heavy-tails as is expected of the stylised facts of financial time series [65]. Since the magnitudes and directions of skewness differ between the two samples, we can also infer time-varying dynamics in the series. Further, we can attribute these differences to the COVID-19 pandemic. These features give credence to our use of the frequency- and time-varying wavelet techniques to examine the interconnectedness of these macroeconomic variables.
Table 2 provides the correlation measure among all the variables. Although this study concentrated on bivariate Morlet wavelets analysis, a simple traditional Pearson correlation measure could provide some insight for deeper co-movement analysis across time and frequency scales. We observe both significant and insignificant correlations among and between the international equity markets, albeit zero correlations. Surprising, the exchange rate does not show any link with the international equity indices. The observation from the correlation analysis shows that the main variables of interest, dollar to cedi exchange rate and the GSEI suggest weak link with international equity markets. However, what is not clear is whether these correlations (as provided by Pearson product moment) remain constant across different times and times horizons. This, precisely, is what the wavelets methodology seeks to address. As explained under the strength of the wavelet approach, the data series are not required to meet some conditions such as normality or stationarity. Further, since the studies examines co-movement among pairs of variables others may suggest a test of co-integration, possibly using the Engle-Granger co-integration test [2,64]. Again, these tests are not needed since they are based heavily on stationarity and normality conditions which the wavelets methodology does not require.
Fig. 2. Daily log-returns series of selected variables.

Table 1
Descriptive summary of variables.

|                | EXC  | GSEI | DVLI | SP500 | COVID-19 |
|----------------|------|------|------|-------|----------|
| **Full-sample**|      |      |      |       |          |
| Observations   | 2437 | 2437 | 2437 | 2437  | -        |
| Mean           | 0.0006 | -0.0002 | 0.0001 | 0.0005 | -        |
| Std. Dev.      | 0.0123 | 0.0130 | 0.0104 | 0.0113 | -        |
| Skewness       | 0.3139 | -0.2475 | -2.2432 | -1.0437 | -        |
| Kurtosis       | 13.4427 | 7.9383 | 31.8781 | 18.1410 | -        |
| Normtest.W*    | 0.7275 | 0.8939 | 0.8033 | 0.8469 | -        |
| **COVID-19 period** |      |      |      |       |          |
| Observations   | 233  | 233  | 233  | 233   | 233      |
| Mean           | 0.0003 | -0.0001 | 0.0012 | 0.0021 | 0.0410   |
| Std. Dev.      | 0.0117 | 0.0097 | 0.0181 | 0.0168 | 0.0989   |
| Skewness       | 0.3866 | -0.8057 | -0.2138 | 0.4249 | 3.9715   |
| Kurtosis       | 7.1009 | 3.9659 | 6.5727 | 5.3401 | 16.9005  |
| Normtest.W*    | 0.7822 | 0.9211 | 0.9017 | 0.9078 | 0.4434   |

* Indicates estimates are significant at the 1% level of significance.
Table 2
Correlation among selected variables for full sample.

|       | EXC      | GSEI 0.030 (0.21) | DVLI 0.010 (0.78) | SP500 0.720 (0.00) |
|-------|----------|-------------------|-------------------|-------------------|
| EXC   | -        | -                 | -                 | -                 |
| GSEI  | 0.030 (0.21) | -                 | 0.010 (0.78)      | 0.720 (0.00)      |
| DVLI  | 0.000 (0.83) | 0.010 (0.78)      | -                 | -                 |
| SP500 | 0.000 (0.97) | 0.010 (0.64)      | 0.720 (0.00)      | -                 |

Note: P-values are in parentheses.

Fig. 3. Bivariate wavelet coherence for pre-COVID-19 period.

Fig. 3. Continued

Results and discussions

Bivariate for pre-COVID-19 period

In this sub-section, we conduct analysis of the interdependence between the macroeconomic variables using bivariate wavelet coherence. As indicated earlier, we split the data into two sub-samples: pre-COVID-19 and COVID-19 periods. Even though a number of structural break tests did not coincide with the pandemic period, it is clear from the literature and fundamental analysis the pandemic has caused shifts in the global financial market. In order to justify that the pandemic has an impact on the interdependence between the variables, we further conduct partial wavelet analysis (Fig. 4-right panel) for the COVID-19 sub-sample period by controlling for confirmed COVID-19 cases. In the same period, the bivariate wavelet coherence (Fig. 4-left panel) is estimated. This helps to ascertain the differences in the comovements, and hence attribute these to the pandemic. The bivariate wavelet coherence pre-COVID-19 period is presented in Fig. 3.
The wavelet coherence (WC) is used as a local correlation while the phase-difference provides information on any lead or lag nexus between the variables. The WC, according to Rösch and Schmidbauer [75], takes into consideration the individual power differences and provides joint periodic properties of the various signals, just like the coefficient of determination. These are given in Figs. 3 and 4 as heatmaps. In these plots, the area of interest is significant at 5% and lays in the cone of influence (COI) within the white contours with the arrows. A red color in the white contours at the right-hand (left-hand) shows a strong co-movement between the two signals at the end (beginning) of the periods while a red color in the white contour at the top (bottom) of the heat map indicates a strong co-movement at high (low) frequencies. For phase-difference between the signals, the arrows are examined. For instance, arrows facing the right suggest the series are in-phase while arrows facing the left show that the series are out-of-phase. In addition, arrows facing right and up (right-up) suggest the first series lags and a right-down means the first series leads. Similarly, a left-up indicates the first signal is leading while left-down shows the first series is lagging [75]. The purpose of these is to draw comparison between Ghana’s equity index and exchange rate market co-movements and international equity indices. The leading and/or lagging relationships point to market strength and they suggestive causal linkages in the time-frequency domain.

From Fig. 3, we observe that there is evidence of joint periodicity in the pairs shown by scattered phase-differences (arrows) in the COI in both time and frequency domains. We also find that the coherencies and phase-differences are non-homogenous (arrows showing down, up, right and left scattered all over in various contours) for all six pairs. From these, it is difficult to tell lead-lag relationships for the variables. Nonetheless, we can find a few mini COIs within the main COIs where discernible lead-lags can be determined. We further note that the discernible patterns are largely in the medium-to long-term horizons across time. These suggest that comovements are weak in the short-term for the variables and are not too strong in the long-term. Such dynamics present avenues for both local and international diversification and risk-minimisation.

For EXC-GSEI pair, GSEI leads out-of-phase (they move in the opposite direction) in the 16–32 frequency band between early 2015 and early 2016. Dominantly, DVI leads EXC out-of-phase within the 60–256 bands in 2012 and 2020. Further, the S&P500 and EXC almost trade-off lead-lag nexus both in-phase and out-of-phase across the board. In the 128–256 band for 2012, the DVI leads GSEI in-phase. It is interesting to see that the GSEI trumps the S&P500 both in-phase and out-of-phase but only in the long-term beyond the 256 frequency and between 2014 and 2018. What is not surprising in the fierce lead-lag contest between the two global pairs; S&P500 and DVI. In summary, we find that the Ghanaian market is largely influenced by the international equity market at various time-horizons. From the varying nature of the coherencies, we can further infer which ones are just interdependence and which ones are contagion as defined in Yang et al. [84]. They indicate that if wavelet coherences are suddenly high at low frequencies (medium- to long-term) at certain periods and the latter are not we term that as contagion. This definition is in tune with Forbes and Rigobon’s [32] definition of contagion as sudden surges in correlations. It is clear from our coherencies that the most the lead-lag relationship occur within the low frequency range (above the middle level – from 64 band). Thus, we infer contagion for the EXC-GSEI, GSEI-DVI, and GSEI-S&P500 pairs (see also the summary in Table 3).

These findings show co-movement between currency prices and equity indices vary across time and frequency and are similar to the results of other studies. For instance, Loh [50] investigated currency and equity indices co-movements among Asia Pacific with US and European equity markets using wavelets and found correlations at low frequency levels. Similarly, Graham et al. [37] look at the same relationship for 22 emerging markets and the US and show that there is high degree of co-movement at low frequencies and the strength of the relationship varies by country. From the above observations over the span of our data, there are couple of lead and lag relationships among the various pairs from medium-high scales at different times in years. However, the phase-difference among the pairs are generally inconclusive over the data period. The above observations are in line with similar Africa studies which examine integration within Africa equity markets and their global counterparts conclude that equity markets in Africa are inadequately integrated within and globally [48,60,15].

![Fig. 4. Bivariate for COVID-19 period and PWC for COVID-19 period with infection rates.](image-url)
Drawing from these smilingly weak and short interdependences showed in the patterns of the various pairs of the economic variables, investors could explore (in short- to medium-terms) exchange rate and GSEI as diversification and hedging instruments with international equity assets, to mitigate the risk and investment exposures of portfolios. In other words, market players can form their investment portfolios by adding assets denominated in cedi/dollar exchange rate and GSEI with other global equity asset categories in short- to medium-terms to reduce loses and maximize investment returns.

As argued by Boako and Alagidede [15], the degree of market integration has implications for shock transmission and whether markets will decouple or recouple from any global shock (like financial) is dependent on the origin and the nature of the shock. The results from the same study show that there was increased correlation between Africa equity markets and international asset classes during the 2008-2009 global financial crises. Among other things, this suggest a critical examination of the same relationship in COVID-19 era, to ascertain the influence of health-related crisis on the co-movement process.
**Bivariate wavelet coherence for COVID-19 period and partial wavelet coherence for COVID-19 period with infection rates**

We re-examine the co-movement of the variables within COVID-19 era. To do this we perform WC for the period and see how they differ from the previous era. It is clear that the comovement in period is influenced by the panic (as measured by the COVID-19 infection rates). There is a general consensus that increasing infections rates are usually associative with fear and panic in the market. Thus, in order to ascertain the actual relationship between the variables, we need to isolate the COVID-19 from the interaction. This is done through the partial wavelet coherence (PWC). In addition, a disparity in the WC and PWC is a statistical test of the impact of COVID-19 on the dynamic interdependence between the variables. These are presented in Fig. 4 (left panel for WC and right panel for PWC).

Summarily, the WC (left panel of Fig. 4) in this period is similar to those in the pre-COVID-19 period in magnitude, direction, and phase-difference. But there are some differences as well, mainly emanating from the calendar time. First, we find that the EXC and GSEI are out-of-phase and GSEI leads in the 16–30 band in July 2020. The DVLI strongly leads the EXC out-of-phase between September and November 2020 in the 16–32 band. Similarly, S&P 500 strongly leads the EXC out-of-phase between September and November 2020 in the 16–32 band. In the long-term between 50–64 band, the DVLI leads GSEI out-of-phase from May to November 2020, but indistinct everywhere else.

However, there is no discernible nexus between GSEI and S&P 500 during the COVID-19 period for the most part. Except that in July 2020 where the former leads in the 4–8 frequency band in-phase. This is similar to the dynamics in the pre-COVID-19 period, but in the short-term. In the case of DVLI and S&P 500, the comovements are same as in the pre-COVID-19 period. There are strong coherencies at different time horizons over the sub-sample period and a mixture of both in-phase and out-of-phase links. As done in the pre-COVID-19 coherences, we infer some episodes of contagion for the following pairs: EXC-DVLI, EXC-S&P500, and GSEI-DVLI.

A general closer scan among these variables shows a little more intense interdependancies during COVID-19 period than before but not widely spread over time. This not case for the EXC-GSEI and GSEI-S&P500 links. The foregoing outcomes presume that COVID-19 pandemic has little influence on the relatedness of pairs of factors in line with the results of Omane-Adjepong et al. [62]. The outcome also corroborates the results in Boako and Alagide [15] that find significant evidence of increase correlation during the 2008–2009 global financial crisis (GFC) in line with the theoretical proposition by Forbes and Rigobon [32] on shift contagion (see, also [63]).
Table 3  
Summary of net lead/lag and phase dynamics from wavelets analysis.

| Pair                  | Time-horizon | Phase (In-/Out) | Lead/Cause | Relationship (Interdependence/Contagion) |
|-----------------------|--------------|-----------------|------------|-----------------------------------------|
| **Pre-COVID-19 period** |              |                 |            |                                          |
| EXC and GSEI          | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Out-            | GSEI       | Interdependence                          |
|                       | Long-term    | Out-            | Indistinct | Contagion                                |
| EXC and DVLI          | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Out-            | DVLI       | Interdependence                          |
|                       | Long-term    | Out-            | DVLI       | Interdependence                          |
| EXC and S&P500        | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Indistinct      | Indistinct | Interdependence                          |
|                       | Long-term    | Indistinct      | Indistinct | Interdependence                          |
| GSEI and DVLI         | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | In-             | DVLI       | Interdependence                          |
|                       | Long-term    | In-             | DVLI       | Contagion                                |
| GSEI and S&P500       | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Indistinct      | Indistinct | Interdependence                          |
|                       | Long-term    | In- and Out-    | GSEI       | Contagion                                |
| S&P500 and DVLI       | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Indistinct      | Indistinct | Interdependence                          |
|                       | Long-term    | Indistinct      | Indistinct | Interdependence                          |
| **COVID-19 period**   |              |                 |            |                                          |
| EXC and GSEI          | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Out-            | GSEI       | Interdependence                          |
|                       | Long-term    | Indistinct      | Indistinct | Interdependence                          |
| EXC and DVLI          | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Out-            | DVLI       | Interdependence                          |
|                       | Long-term    | Indistinct      | Indistinct | Contagion                                |
| EXC and S&P500        | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Out-            | S&P500     | Contagion                                |
|                       | Long-term    | Indistinct      | Indistinct | Interdependence                          |
| GSEI and DVLI         | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Indistinct      | Indistinct | Interdependence                          |
|                       | Long-term    | Out-            | DVLI       | Contagion                                |
| GSEI and S&P500       | Short-term   | In-             | GSEI       | Interdependence                          |
|                       | Medium-term  | Indistinct      | Indistinct | Interdependence                          |
|                       | Long-term    | Indistinct      | Indistinct | Interdependence                          |
| S&P500 and DVLI       | Short-term   | Indistinct      | Indistinct | Interdependence                          |
|                       | Medium-term  | Indistinct      | Indistinct | Interdependence                          |
|                       | Long-term    | Indistinct      | Indistinct | Interdependence                          |

On the side of exchange rate and the local stock market, the empirics on the link between exchange rate volatilities and stock market is generally inconsistent [55]. As stated by Yucel and Kurt [85], the direction and nature of the link is dependent on the exchange rate regime practiced. According to the same authors, floating exchange rate appreciations hurts the attractiveness of export markets which negatively affects the domestic equity market. Contrary, for import driven economies, exchange rate appreciations may positively influence the equity market by reducing input costs. One of the early studies on the exchange rate and equity returns in Ghana is Adjasi et al. [2]. They use the exponential generalised autoregressive conditional heteroskedascity model to establish the relationship between exchange rate volatility and stock returns and found a negative relationship between the two assets; implying a depreciation of the cedi leads to an increase in the GSE returns. Although this finding agrees, partly, with the results in this study, the relationship is not persistent over time but rather at some short time span at short to medium frequency scales. As rightly reported by Owusu Junior et al. [64], the two series are generally, out-of-phase with mix interaction of lead-lag nexus, often, at lower frequencies. The short time-span interconnectedness is less profound during COVID-19 with the stock index leading.

We further discuss the PWC to determine the impact of the pandemic on the interdependencies. To understand the PWC plots, we look out for the concentrations of coherencies and compare them with WC. We have places them side-by-side for easy comparison. While the PWC plots do not show phase-difference [42], no correspondence in the location of COIs indicate an impact of the controlled variable (COVID-19 cases) in the PWC. From our plots, it is very clear that effect of COVID-19 cases on the link between the variables is very minimal in most of the pairs. This is seen from the similar location of COIs in both and frequency. There is only a marked difference in the EXC and S&P500 pair where the PWC records high coherence in the 60-64 band in September 2020, but no coherence at all in the WC. It does imply that when the infection rates affected the correlation between EXC and S&P500 in the long-term. This does not come as surprising since the pandemic affected the US market strongly and hence their currency which is a major trading partner and determining factor for the volatility of the Ghanaian cedi.
Fig. 5. a: WMC and WMCC for pre-COVID-19 period. b: WMC and WMCC for COVID-19 period. Note: upper panel - COVID-19 period, lower panel - for COVID-19 with infection rates.

Multivariate wavelet for pre-COVID-19 and COVID-19 periods

In order to see the composite relationship among all the variables at once, the WMC and WMCC is useful. It solves the difficulty of comparing all the pairs of coherencies in the bivariate wavelet case. These are presented in Fig. 5a (for pre-COVID-19 period) and 5b (COVID-19 period). Fig. 5b has two parts; upper panel and lower panel which has COVID-19 infection rates as an additional variable. We do all these to ascertain the impact of the pandemic on the interactions between the variables.
The WMC (on the left of Fig. 5a,b\(^1\)), show generally increasing correlations from scale 1-16 (short- to medium-term) from about 70 to 80% and declines to about 60% in the long-term in the pre-COVID-19 period. But for the COVID-19 period in Fig. 5b, WMC increases from about 68 to 99% in both cases across the scales. This supports the findings of Das et al. [24] and the consensus in the literature that interdependence increase during crisis periods and hence reduction in diversification benefits.

In the WMC (Fig. 5b, on the right side), we can find the market leaders (dashed lines on negative lags), laggards (dashed lines on positive lags), or potential leaders/laggards (dashed lines on zero lag) at various scales. For the pre-COVID-period, we find that dominance of DVLI in lagging all the others between scales 16 and 32 which corresponds to the medium- to near-long term with very high correlations. In the long-term WMC lags all other markets. This is not surprising given the size of the Ghanaian market. In the short-term, DVLI also exhibits potential to lead/lag on three scales and the S&P500 on scale 4.

In the COVID-19 period, the WMC show the complete dominance of the DVLI with market leadership in the long-term and potential lead/lag at all other scales. The dynamics change only a little when the COVID-19 infections are included. We find that DVLI becomes a laggard instead of leader in the long-term. It possesses potential lead/lag power at all other scales except for scale 2 where the S&P500 is a potential lead/lag. It is clear that the COVID-19 pandemic has affected the interrelationships among these variables. First, we find that the strength of the Ghanaian exchange rates market is wiped out completely during the pandemic. Second, the pandemic is able to shift the dominant market from a leader to a laggard. These bring to the light the effect of the COVID-19 pandemic as in other crises to alter the dynamics of financial markets (see [32,52,63]).

**Conclusion**

In this study, we probe deeper into the co-movement of equity and exchange rate with relation to other international markets and further determine whether exchange rate and equity index volatilities are driven by market characteristics or global uncertainties such as covid-19. The variables used in this study are Ghana cedis/dollar exchange rate, Ghana Stock Exchange composite index, S&P500 index and FTSE developed index. Although the literature on this subject is mixed and market-dependent, there is a consensus that Africa markets exchange rate and equity indices have little or no link with international equity markets. Specifically, we re-visit this relationship for the Ghanaian market.

We digress from the usual econometric models, as seen in the literature, to investigate this subject by using a modern and much more dynamic advanced econometric model known as the wavelet analysis. The study employs a 3-dimentional continuous Morlet wavelet transform which has desirable features and efficiently captures co-movements by localizing within the time-frequency domains compare to the traditional models. In short, the novelty in this study rest in the methodology used and the COVID effect analysis.

The analysis from the study reveals that the dynamics of co-movement or interconnectedness of exchange rate and Ghana Stock Exchange composite index has evolved over time and also across frequencies. The outcome of the various analysis unearths some interesting results. First, the cone of influence, as shown by the wavelet spectrum, does not cover the entire data frequency (slightly above the 512 scale-2 years), which suggests that long-term forecast of exchange rate and equity index in Ghana beyond four years could be misleading, since significant levels of interdependences are concentrated around the mid-team scales.

Second, there is some evidence (not widely spread though) to support a low-medium term lead-lag connections between exchange rate and GSEI which suggest a near weak association between these two markets. Hence, within the Ghanaian financial markets, investors can consider investing in the dollar and the GSEI pair to enjoy diversification considering the direction and duration of these assets. Third, the co-movement between exchange rate or GSEI and international equity markets show a similarly weak association. Thus, both domestic and international investors can consider the Ghana cedis/dollar rate and GSE equity index as possible safe havens or hedging instrument for their medium-term investment. However, it is worth noting that, at a higher frequency band, the GSEI relates strongly out-of-phase with the S&P500 index implying a better diversification option among the equity options. These observations are similar to works by Dahir et al. [22] and in direct consonance to the finding of Owusu Junior et al. [64].

Four, a closer scan of the interdependencies among these variables show high energy during COVID-19 than during the non-COVID-19 period but is not widely spread over time. The foregoing outcomes presume that COVID has little influence on the relatedness of pairs of factors. Finally, we observe a strong co-movement between the rise in COVID cases and exchange rate at higher frequency scales where exchange rate lags out-of-phase. As expected, a rise in COVID cases negatively affects the cedi/dollar exchange rate.

The research reveals very interesting information about Ghana's equity and foreign change market. For policy direction on exchange rate and GSE market, we recommend that policy makers consider the time and frequency dimensions of these assets as traded on the various markets. Besides, institutions and strategic investors must also consider the time and frequency characteristics of both exchange rate and the equity index as they pursue value maximization drive, as evident in this work and other related studies. Furthermore, global uncertainties (like COVID) deepen, to some extent, the co-movements

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\(^1\) Correlations are in black flanked by upper and lower confidence estimates in blue.
between exchange rate-GSEI and how they relate to other international assets, suggesting a careful policy and investment strategies and regulation around or during periods of global market uncertainties. In addition, Ghana’s currency and equity markets are somewhat segmented from the volatilities of the dollar and equity markets of advanced economies. This provides a better diversification opportunity for investors to consider building their portfolio across cedi denominated assets and also on the equity market without worrying about international equity and dollar volatilities. This is more beneficial to investors with a medium to long term investment horizon since the identified co-movements are identified mostly in higher frequency domains.

Finally, while wavelets intrinsically lead/lag suggest causality, further parametric non-linear causality such as those of Diks and Panchenko [26,27] and Bai et al. [9] can be explored. As parametric tests, they provide more interpretable and quantifiable relations at the frequencies and across time. Last, and pursuant to policy initiatives and their news, information spillovers are also a pertinent factor to consider in currency markets interdependence and contagion.

Declaration of Competing Interest

The authors of this study declare that they have no conflict of interest and no financial assistance was received from any person or group of persons for this study.

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