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# African and international financial markets interdependencies: Does Covid-19 media coverage make any difference?

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ABSTRACT

This study examines the co-movement and time-varying integration between equity, exchange rate, and international market volatility indices across different time–frequency domains using - bi-partial wavelet, - supplemented by dynamic conditional correlation-generalised autoregressive conditional heteroskedasticity (DCC-GARCH), - and BEKK GARCH model for selected African countries. First, the findings indicate that the co-movement between equity and exchange rates during the pandemic was exacerbated by global COVID-19 media coverage. The findings indicate that there has been a substantial risk transfer between exchange rates and stock returns during the COVID-19 pandemic, resulting in a decline in domestic stock returns and subsequent capital outflows, which in turn increased the exchange rate. Given the growing difficulties in diversification, specific information on the volatility of financial market connectedness is required to plan hedging strategies. To explore the influence of global market volatility on Africa's equity and currency markets, it is crucial to analyse the relationship between regional and global market fluctuations, especially given the negative impact of the COVID-19 pandemic. Our empirical research demonstrates that the VIX and OVXCL indices play a significant role in transmitting spillovers to currency and equity markets in Africa. This suggests that the sentiment indicators provided by the VIX and OVXCL can be useful in predicting the behaviour of Africa's currency and equity markets.

## 1. Introduction

In the field of finance, diversifying investments is a fundamental principle that plays a crucial role in minimising risk in a portfolio. Investors are frequently advised to diversify their portfolios by allocating their assets across different sectors, stocks, and nations that exhibit low correlations with one another (Aharon et al., 2022). A plethora of studies have shown that systemic risks, such as the Great Financial Crisis of 2007 and the recent COVID-19 pandemic, coupled with the growth of international capital markets have led to increased interconnectedness among countries (Naeem et al., 2020; Raddant & Kenett, 2021; Greenwood-Nimmo et al., 2021; Lang et al., 2024). The interconnectedness could potentially undermine the notion of the perks associated with investing in diverse capital markets (Armah & Amewu, 2024). It's worth noting that historical events have demonstrated that during periods of market volatility, the relationship between different markets becomes more entwined. This insight has prompted researchers to concentrate on the interdependence, co-movement and connectedness of assets.

The study of interdependence, co-movement and connectedness during systemic risk across a broad spectrum of financial markets, including equities, fixed-income securities, and commodities across diverse economies, has been the subject of extensive and growing research (Khan et al., 2023; Umar et al., 2023; Billah et al., 2023; Umar & Teplova, 2024; Ferrer et al., 2021), During the period of economic difficulty, investors regularly rely on financial statements and industry reports to make well-informed decisions. Nevertheless, during a systemic risk like the COVID-19 pandemic, investors might not have access to the necessary information to evaluate the situation accurately (Bai et al., 2023). Consequently, media reports become the primary source of information for investors as they can significantly affect investor sentiment and market performance (Aharon et al., 2022).

Similarly, excessive media coverage of the current state of the epidemic can intensify public opinion, which may subsequently impact

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investors' mindsets and contribute to a heightened sensitivity among them resulting in the spread of fear (Lyócsa et al., 2020). This health-related systemic risk presents a clear illustration of the detrimental and pervasive consequences that have resulted from a crisis in global capital markets (Aharon et al., 2022), while also demonstrating the impact of heightened interconnectedness across assets and nations. Unlike previous crises, COVID-19 stands out as a worldwide crisis that originated outside of financial markets but has nevertheless had a profound effect on every country directly or indirectly. The way that the risk of contagion has spread from one country to another mirrors the manner in which the virus itself has spread (Aharon et al., 2022). During times of economic uncertainty, investors often turn to alternative markets, particularly emerging markets, to diversify their equity portfolios or seek a safer haven.

The empirical research on emerging markets, such as African markets, has shown a weak co-movement between local markets and their international counterparts. However, the impact of market sentiment and its potential to increase the systemic risk induced by covid-19 pandemic on these correlations remains largely unexplored. This highlights the importance of re-evaluating the dynamics of market co-movement and interconnectedness in emerging markets, especially in the context of the COVID-19 pandemic. Consequently, examining interdependence and contagion effects during health-related systemic risk offers a unique opportunity to observe the mechanisms of risk transmission and co-movement within the market. This paper seeks to investigate the interdependence, co-movement and connectedness of stock price-exchange rate nexus and contagion effect during COVID-19.

Our research connects with studies focusing on the transmission of risks during health systemic risk, specifically those examining the contagious impacts within the currency and stock market. As equity markets have become more integrated, they have developed a stronger connection to other markets and have facilitated significant international financial flows. This has resulted in equity markets having a growing influence on exchange rates, which can help to explain some of the excess volatility in foreign exchange markets during health-related systemic risk. The existing literature by Amewu et al., (2022), Agyei et al., (2022), Li et al., (2022), Narayan et al., (2020), and Sharma et al., (2021) demonstrated that exchange rate-stock returns vulnerability to global economic shocks and uncertainties creates a strong possibility of co-movement. This demonstration, in turn, has inspired a vast literature focusing on modelling currency-equity price volatility with an emphasis on market uncertainties (Nkrumah-Boadu et al.,2024; Abid, 2020; Hoque & Zaidi, 2019). The interdependencies between the nexus have profound effects on risk reduction and profits through international portfolio diversification strategies.

However, as opposed to previous studies that concentrated on currency-stock prices and COVID-19[1]nexus (Amewu et al., 2022; Narayan et al., 2020; Agyei et al., 2022), this paper, hypothesises that market sentiment will exacerbate the impact of the pandemic on currency-stock price co-movement. Behavioural finance literature offers numerous instances where media tracking is utilized to evaluate both the intricate behaviour of society and that of the financial market (Umar & Gubareva, 2020; Bukovina, 2016; Umar & Gubareva, 2021; Yang et al., 2019). Generally, all these studies concur that media tracking serves as a potent means of data collection, concentrating on less rational factors such as market sentiments of investor communities, the public mood at the societal level, and various other behavioural drivers.

To empirically examine interdependence and co-movement between the nexus, we follow Umar et al. (2021a) by obtaining historical information about the media coverage index(MCI) behaviour from the Raven pack data analytics platform. The MCI, as determined by Raven Pack, calculates the COVID-19 coverage percentage on social media in relation to news providers that focus on COVID-19 themes and concerns, as a proportion of all media content providers. The MCI, serves as a comprehensive measure of the COVID-19 developments and their influence on the overall morale and sentiment of society (Umar et al., 2021b), capturing the fluctuations in coronavirus awareness among financial stakeholders. The motivation for this hypothesis is based on varying results (see (Alimi & Adediran, 2023; Amewu et al., 2022; Agyei et al., 2022; Narayan et al., 2020) of recent empirical studies on currency-stock prices during the pandemic period. The objective is to see how MCI has shaped or influenced the co-movement and interdependence in which the nexus has been traditionally believed (see Amewu et al. 2022; Agyei et al., 2022;;Narayan, 2022; Okorie & Lin, 2021; Li et al., 2022; Narayan et al., 2020; Sharma et al., 2021).

First, we add to this strand of literature by incorporating media sentiment to the co-movement of currency-stock price co-movement during this unique period marked by great uncertainty in the global financial market. To do this we employ bivariate and partial wavelet analysis to investigate the co-movement between nexus. This technique, unlike other econometric models like GARCH models, provides a significant advantage in performing localized analysis of a specific area or signal within a larger image or dataset (Armah & Amewu, 2022). By focusing on this smaller area, wavelet analysis can reveal aspects of the data that other analysis techniques may miss (Afshan et al., 2018). Financial markets are known to experience fluctuations at various time intervals. Previous studies have utilized time-domain approaches to analyze associations within the financial markets. However, these associations can not only vary across frequencies but may also change over time. The method used in this study can help uncover economic time–frequency associations that have not been detected so far.

Second, the COVID-19 pandemic brought about uncertainties in financial markets that significantly impacted the development of the global economy, highlighting the importance of addressing systemic risks (Armah & Amewu, 2024). The unpredictable changes in market volatility can lead to increased risk volatility in financial markets (Xiao et al., 2021). Given the aforementioned information, it is difficult to gauge the market risks and projections for futures markets (Liu et al., 2013). However, some researchers have confirmed that the implied volatility index can more accurately estimate market uncertainties and risks (Xiao et al., 2021; Xiao et al., 2019). Thus, the application of implied volatility to gauge the relationship between investor panic and anticipated market volatility can serve as a reliable indicator for assessing systemic market risk (Chen et al., 2022). In doing so, we extend our work by considering market variations and exploring these connections across different levels of market volatility. The motivation stems from the prevalent argument in the literature that the responsiveness of exchange rates to the dynamics of stock prices responds to changes in international market volatility. Our primary interest lies in examining volatility interconnectedness and transmission between exchange rate-stock returns in Africa and implied volatility. Our approach stands out from previous works (see Chen et al., 2022; Ji & Zhang, 2019; Plíhal & Lyócsa, 2021; Y. Liu et al., 2019; Antonakakis et al., 2023; Li, 2022; Xiao et al., 2019) who employ heterogeneous autoregressive model, GARCH-MIDAS, Markov switching vector correction model, TVP VAR, and quantile regression. The focus of our second contribution is volatility connectedness and spillover between the African market and implied volatility before COVID-19 and during the pandemic-induced crisis.

Methodologically, our study adopts a distinct econometric approach to investigate the dynamics of exchange rate-stock returns and implied volatility. First, we use the volatility decomposition method of Danielsson et al., (2018) and DCC-GARCH connectedness approach to estimate the high volatility and low volatility spillover effect between implied market volatility and Africa exchange rate-stock prices. One of the primary benefits of high-low volatility spillover networks is that they provide an efficient means of capturing the diverse volatility spillovers

[1] The use of daily confirmed cases, number of death as a proxy COVID data has a lot limitation making cross countries comparison of the raw data and policy response difficult. see Alvarez et al., (2023) for comprehensive literature.

during systemic risk (Xiang & Borjigin, 2024). This method enabled a nuanced understanding of the interconnectedness and spillover effects between market volatilities and the African market, while also shedding light on the market Integration systemic risks. Market volatilities have been touted to have a ravaging impact on financial markets (Amoako et al., 2022; Boateng et al., 2021) from which Africa's financial market could be more sensitive as a result of contagion effect from market interaction.

For the purpose of measuring market risk, we utilize the CBOE VIX as a quantifiable rough proxy. This measure is determined by averaging the weighted prices of S&P 500 call and put options that have 30 days remaining until expiration. Consequently, it is commonly utilized by investors as a projection of the short-term volatility of equity prices and is not noticeable when the VIX is low, i.e., in tranquil market conditions. However, it becomes highly evident during tumultuous, high VIX periods. In order to demonstrate this hypothesis, we investigate how the S&P 500 index and COBOE euro currency EFT volatility index (EVZCLS) respond to changes in Africa market. Subsequently, we construct a high-low spillover network between implied volatility stock returns-exchange rate based on the high and low volatility sequences. Our analysis focuses on the systemic risk accumulation phase (low-volatility) and (high-volatility) separately, with the aim of accurately identifying the sources of risk accumulation and outbreak, as well as the corresponding risk transmission mechanisms. This information is crucial for regulatory authorities to identify key areas for systemic risk prevention. Given the increasing interest in Africa financial market among investors it is crucial to examine their susceptibility to external shocks. Our empirical analysis emphasis the importance of constructing reliable portfolios among market volatility indices as transmitters of external shocks and Africa market. It will also provide investors in Africa stocks with the chance to rebalance or reconstruct their portfolios to include market volatilities. Additionally, observing the spillover and connectedness effect of implied market volatilities allows investors in Africa market to hedge against the transmission of shocks, potentially preventing contagion effects and guiding their investment decisions.

Our third contribution is inspired by the literature that examines the impact of high and low stock market volatility (Danielsson et al., 2018; Xiang & Borjigin, 2024). According to this literature, systemic financial risk has two dimensions: time and space. Risk contagion is the fundamental aspect of systemic financial risk in both time and space dimensions. With respect to the time dimension, systemic financial risk focuses on its formation and evolution process, which can be divided into two stages: risk accumulation and risk realization (Xiang & Borjigin, 2024). Specifically, the accumulation stage of systemic financial risk occurs during a period of low volatility when asset prices fluctuate less. In contrast, the outbreak stage of systemic financial risk is characterized by an overall increase in asset price volatility (Xiang & Borjigin, 2024). Our study makes several significant contributions. To begin with, we contribute to the comprehensive examination of risk spillovers between market volatilities and exchange rate-stock price for the Africa market. Drawing on two dimensions of risk accumulation and risk outbreak (Danielsson et al., 2018), we propose an innovative high-low volatility spillover network analysis framework that goes beyond the existing research, which only considers homogenous volatility spillovers between exchange rate and stock prices (Hussain et al., 2024; Herley et al., 2023). Notably, each network layer in our proposed method is independent and contains distinct connectedness information. We employ DCC-GARCH to evaluate the characteristics of high-low volatility networks from both static and dynamic perspectives, providing a deeper understanding of risk spillovers between Africa and the international market.

More so, the motive of the sample selection comes from the fact that African markets are vulnerable to shocks from the global financial market (Boako & Alagidede, 2018), which may lead to currency fluctuations and forces them to frequently intervene in foreign exchange markets to mitigate currency fluctuations. It is worth noting that, despite long-standing beliefs that African stocks may offer diversification opportunities, Anyikwa & Le Roux (2020) posit that in the event of a crisis in the global financial market, Africa's markets are also significantly affected due to the role of media coverage (Bossman, Teplova, et al., 2022). However, promoting real and financial integration has increased their exposure to external shocks, which has raised various challenges for policymakers. On the contrary, the transmission of shocks of volatility and multiple systemic risks and the resulting instability of the market is one of the potential challenges during the turbulent period. With a substantial contribution to the global economy, it is imperative to establish the link between the African financial market and international market volatility indices in order to inform market participants about the influence and behavioural factors that tend to impact economic expectations during the COVID-19 pandemic.

Finally, the outcomes of our study have significant implications for decision-making in the areas of investment and risk management, particularly for international investors, regulatory authorities, and policymakers. For investors in emerging markets, exchange rates offer opportunities for diversifying their investments in developed economies, as the value of developed-country currency moves in the opposite direction to developed-country equity returns. This helps to cushion against extreme fluctuations in equity returns. However, for investors in developed markets, diversification opportunities for their emerging market investments are limited, as the value of emerging-market currency tends to move in tandem with equity returns. For monetary and supervisory authorities, our empirical framework can be used to create tailor-made stress-test scenarios that take into account exchange rate and equity dependence, helping to protect economies against system risk.

The remainder of the paper is as follows; Section 2 describes theoretical and empirical review. Section 3 describes the method, material, and preliminary results. We present our main results in Section 4 and conclude with the practical implications of policy and recommendations in Section 5.

## 2. Theoretical review

Our research is rooted in various economic and financial theories, notably the theory of interdependence and Flow and the stock-oriented model.

### *Flow and stock-oriented model*

The theoretical foundations for analyzing the relationship between stock prices and exchange rates have been firmly established and may be traced back to Dornbusch and Fischer's (1980) influential work, particularly their 'flow-oriented' exchange rate model. These models posited that exchange rates impact international competitiveness, with the flow-on effect being felt in current accounts, and reflected in the effects on real output and incomes. Stock prices are also influenced by exchange rates, as they represent present values of firms' future cash flows. As stock prices fluctuate, they can impact not only future income but also current investment and consumption. In addition, there are stock-oriented exchange rate models, as exemplified by Branson (1981) and Frankel (1983), which view exchange rates as determined by supply and demand for assets. Given that asset valuation and pricing depend on present values of future cash flows, exchange rates are directly linked to asset prices. Although both approaches have a strong theoretical foundation for a specific market, it is essential to empirically investigate the relationship between them since a market response is simultaneous. This means that the market can be influenced by both approaches and a feedback association is possible to appear (Afshan et al., 2018). Under these circumstances, the theory alone may not be sufficient to make inferences about the relationship between the variables, and therefore, an empirical investigation needs to be established during health systemic risk to ascertain the co-movement between the two assets.

### 2.2. Interdependency theory

The theory asserts that there is a direct relationship between financial markets, whereby changes in one market can lead to corresponding changes in a related market (Asafo-Adjei et al., 2021). To ensure interdependence, changes in market dynamics for one asset or market are directly mirrored in the other. The extent and nature of these changes are often comparable, as both markets share similar characteristics (Rosecrance et al., 1977) Rosencrance et al. identify two forms of market interdependence, namely horizontal and vertical. Horizontal interdependence pertains to the magnitude of transactions between two markets in terms of the exchange of goods, capital, etc. On the other hand, vertical interdependence signifies the proportional reaction of economies to changes in the prices of input factors. Given that horizontal interdependence involves the movement of funds between markets, it is the most appropriate form for this study.

The interdependency theory, to a large extent, captures both financial market integration and international portfolio theories, as indicated by Shadlen, (2005). This suggests that the interdependency theory is supported by financial market integration and international portfolio theories. Financial market integration links economies and fosters alliances between them, which many governments aim to preserve (Doyle, 1997). The international portfolio theory facilitates the flow of funds between financial markets due to shared trading values and norms (Polachek, 1980). The aforementioned above aligns with the concept of horizontal interdependence, which Rosecrance et al. ( (1977) assert that it implies connectedness. Therefore, we utilize the theory of interdependence, particularly horizontal interdependence, to investigate the interconnectedness between Africa and the international market.

### 2.3. Empirical literature

In this section, we provide a review of the relevant literature on the subject matter. To achieve this, we have categorized the literature into two distinct branches. First, we review the literature on COVID-19 and currency-stock prices and then we present a review of volatility interconnectedness and transmission between exchange rate-stock prices in Africa and implied volatility.

### 2.4. Currency-stock price during COVID-19

Previous research has produced varied results regarding the impact of exchange rates on stock prices, with some studies supporting and others contradicting this relationship. As the literature on this topic is extensive, we do not aim to provide a comprehensive review here. However, we recommend referring to papers such as (Salisu & Ndako, 2018; Djeutem & Dunbar, 2022; Hau & Rey, 2006; Heimonen et al., 2017; Afshan et al., 2018; Cenedese et al., 2016; Ojea-Ferreiro & Reboredo, 2022) for a more in-depth analysis of the existing research. Our focus of the study is to verify whether or not transmissions between two asset markets; the foreign exchange market and the equity market, during health systemic risk could engender different types of spillovers and contagion compared to other systemic risks and calm periods. Agyei et al., (2022) investigate the relationship between exchange rate returns and stock returns in Africa during COVID-19 in both the time and frequency domains. Their findings reveal that COVID-19 does not heighten the strength of the relationship between currency-stock price returns in Africa, but it does lead to a significant change in the lead-lag relationship between the two assets. The studies find a strong likelihood of high market integration between African markets in the long run, regardless of market conditions. In general market conditions, South African (Namibian) equities take the lead/lag position in the short and long run (intermediate-term). Namibian stocks respond first to shocks among all other variables in the intermediate term, while in the long term, the South African currency market is the last to experience shocks. Conversely, Amewu et al., (2022) posit that there is strong co-movement between a rise in COVID-19 cases and the exchange rate at a higher frequency scale where the exchange rate lags the equity index for Ghana and out-of-phase in the long run. Narayan et al.,(2020) explore the relationship between the Japanese Yen and the nation's stock returns. By employing various econometric models and empirical specifications, the studies found that a decrease in the value of the Yen relative to the US dollar resulted in an increase in Japanese stock returns. Specifically, one standard deviation decrease in the Yen during the COVID-19 period (equivalent to a 0.588 % change) led to a 71 % increase in stock market returns. Notably, this relationship was stronger during the COVID-19 period (January 2020 to August 2020) than in the period preceding the crisis. The finding of Alimi & Adediran, (2023) study confirm the theoretical concepts that indicate a negative relationship between stock prices and exchange rates in advanced and emerging economies. However, their study suggests that this relationship became more pronounced during the COVID-19 pandemic. The key point highlighted by the literature discussed above is that COVID-19 has significantly impacted virtually all aspects of financial and economic systems that have been studied so far. The lack of conclusive findings demands additional scholarly inquiry. In this study, we suggest that the sentiment of the market will intensify the influence of the pandemic on the relationship between currency and stock prices. The extensive dissemination of information about COVID–19 could possibly sway the emotions of investors, especially if they tend to overreact to such data during periods of stress (Barberis et al., 1998). Research by Fang & Peress, (2009) demonstrates that media coverage affects stock returns. Tetlock, (2007) found that negative media coverage has a detrimental effect on stock prices. Prior studies indicate that the sentiment of news can be beneficial for investors when it comes to allocating their assets (Griffith et al., 2020; Frijns & Huynh, 2018). However, none of the previous studies have examined the moderating role of media coverage of COVID-19 using a bi-partial wavelet for the nexus. This therefore provides the grounds for the present study.

### 2.5. Volatility transmission between market uncertainties and currency-stock prices

Volatility transmission in global financial markets is a crucial and unavoidable consequence for international portfolio investment and diversification. The increasing integration and financialization of these markets have necessitated that practitioners and researchers pay attention to the dynamic interconnections among financial markets over the past few decades. It is essential to recognize that the implications of volatility transmission extend beyond just the financial sector, making it a critical area of focus for those involved in investment and risk management. A number of studies in the literature have investigated the relationship between currency, uncertainty, and stock markets. However, these studies have not primarily focused on the impact of volatility transmissions such as implied volatility, on the connection between currency rates and different asset classes, in this case, stocks. Additionally, other empirical works have explored various connections between the stock market, exchange rates, economic policy uncertainty, the CBOE volatility index, and the crude oil volatility index (Abid, 2020; Bartsch, 2019; Hoque & Zaidi, 2019; Egbers & Swinkels, 2015). Wen et al., (2019) scrutinized the nexus between economic policy uncertainty, CBOE volatility index, and crude oil volatility index with key macroeconomic variables by employing a nonlinear cointegrating ARDL model in China. Their empirical results demonstrated that, with the exception of crude oil volatility index, the variables were interconnected. Evidence suggested that the CBOE volatility index played a pivotal role in fueling uncertainty in China's macroeconomy in the long run. However, economic policy uncertainty and crude oil volatility index also had an impact on the inflation rate, GDP, and money supply, and contributed to uncertainty in the economy. Nkrumah-Boadu et al., (2024) investigate the degree of interconnectedness between currency-stock prices and the influence of some selected uncertainty indices using bi and partial wavelet approaches. The partial wavelet analysis indicates a significant effect of global economic policy uncertainty, implied oil market volatility, and volatility index in driving the movements observed in the currency and stock markets. The study also found that the stock market has a significant impact on the currency market, highlighting the need for effective stock market policies. Also substantial work has been done to check the impact of COVID-19 on the financial market and volatility connectedness (see (Ali et al., 2022; Fasanya et al., 2021; Bouri et al., 2021; Antonakakis et al., 2023; Cagli & Mandaci, 2023).

Few studies have examined the volatility spillovers between implied volatility indices and currency-stock prices which are forward-looking measures of market volatility. Prior research has also highlighted the superiority of implied volatility indices over historical volatility indexes in predicting market volatility (Plíhal & Lyócsa, 2021). Our study augments and enriches the existing body of literature by presenting a fresh viewpoint on the connectedness between implied volatility and currency-stock prices. Given that volatility is a measure of how the market responds to and incorporates new information, examining its transmission pattern could offer valuable insights into the features and dynamics of foreign exchange and stock markets. Therefore, given that the information gathered would offer a gauge of these markets' vulnerability, we believe that empirically examining volatility spillovers between market uncertainties and currency-stock prices is relevant. Furthermore, during crises, markets' volatilities tend to rise rapidly, and financial analysts appear to believe that volatility shocks in one market can easily impact the other markets (Fernández-Rodríguez & Sosvilla-Rivero, 2020). Thus, the connectedness analysis is well-suited for testing net directional spillovers, identifying when and where they originated in a given market and how they subsequently spread to the rest of the markets.

In a financially gloomy setting, market sentiment plays a crucial part in shaping investors' actions. Thus, to ascertain the moderating role in COVID-19 media coverage between the currency-stock price, we hypothesis that: $H_0$ COVID-19 media coverage does not moderate the co-movement between currency and stock prices.$H_A$ COVID-19 media coverage moderates the co-movement between currency and stock prices. On the other hand, the global economy has experienced unprecedented level of uncertainty due to the COVID-19 pandemic, which subsequently had a substantial influence on the financial markets. Thus, we hypothesis that does global market uncertainties play a crucial role in the connectedness of financial market in Africa? Fig. 1 demonstrate the transmission mechanism by which the variables are connected.

Finally Van der westhuizen et al., (2022) contend that volatility spillover is more pronounced during health systemic risk confirming the hike in contagion during the period of turbulence hence a ternary of DCC and BEKK GARCH model was employed to investigate the volatility spillover between the exchange rate and stock return. The selection of this model was based on its ability to effectively combine conditional variance and time-varying correlation between the two variables. Our research paper makes a valuable contribution to the existing body of literature on the effects of world COVID-19 on the financial market (stock prices and exchange rates), as well as to the literature on the health systemic risk contagion. In particular, it enhances the current understanding of the economic impact of COVID-19 on these issues.

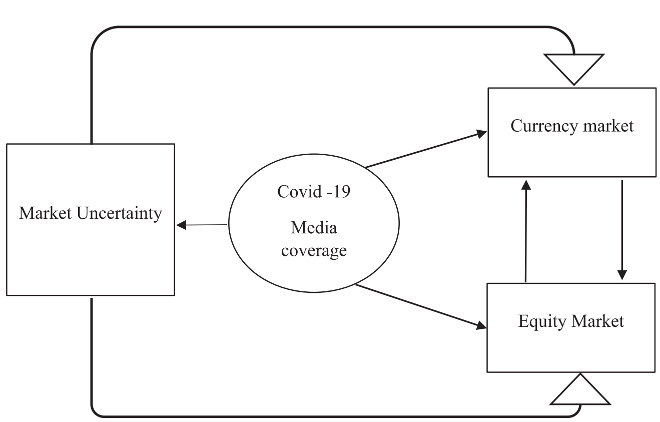



**Fig. 1A.** Conceptual framework. *Source: Authors compilation.*

## 3. Methodology

In this section, we highlight the key methodologies used in our study. To assess interdependencies and co-movement between exchange rate-stock returns we utilise bivariate and partial wavelet coherence characterised by localization in the time–frequency domain to co-movement between the series. To investigate volatility spillover and connectedness between market volatilities and exchange rate-stock returns, we use Hodrick & Prescott, (1997) to decompose the series into high and low. The output generated from decomposition was used as input data for the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) method postulated by Gabauer, (2020) to examine volatility interconnectedness of implied market volatility and equity-exchange rate return in Africa. All the methods employed are essential in evaluating the extent to which equity and exchange rate interdependence have evolved during the financial imbalance occasioned by COVID-19. To begin with our first approach, the application of wavelets is described as follows.

### *3.1. Bivariate and wavelet coherence*

The fragility of Fourier transformations gave rise to the concept of wavelets. Fourier transforms, which provide frequency information on a signal by giving the magnitude of the frequency, are unable to provide information on when a frequency of a specific magnitude exists in time and space. Therefore, Fourier transforms are used for stationary signals but cannot give frequency information on localized signals in time and space. Regardless of the fact that short-term Fourier transforms endeavoured to assist in the solution of this problem, it is still unclear what frequency exists at which point in space and time. The STFT (short-term Fourier Transform) can only tell us what frequency bands (not specific frequencies) are present at specific time intervals. Wavelets, on the other hand, assist in resolving this issue. In contrast to other models that focus solely on time, wavelet analysis evaluates the behaviour of data in both time and frequency domains. It has the ability to evaluate variables at varied frequencies in order to investigate the finer points of joint movements over a range of time horizons without distorting the data. Because of its capacity to give a superior trade-off between detecting discontinuities and oscillations in time series data, the wavelet technique is best suited for numerous financial data analyses. Furthermore, the wavelet approach does not require pre-treatment of the data series and simply decomposes the data into several time–frequency components, which protects against any anomalies in the data structure and loss of important information (Armah et al., 2022; Amewu et al., 2022).

There are two main types of wavelet transform; continuous and discrete wavelet transforms (Madaleno & Pinho, 2012). However, there are several modifications to the mother wavelet. Examples include Morlet wavelets, Gabor wavelets, Shannon wavelets, etc.

However, the focus of this work will be on the most fundamental and often utilized wavelet types in finance: "the mother wavelet," "the Morlet wavelet," and "continuous and discrete wavelet transforms.". CWT has better characteristic extraction than DWT, reducing noise and compressing data. Therefore, CWT is considered an appropriate wavelet transformation for this study.

The decomposition of the wavelet transformation function into an essential function usually consists of the parent wavelet containing the location, time (i) and scale (s) parameters, and is defined as follows:

$$\psi_{\tau,s} = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

where $\frac{1}{\sqrt{|s|}}$ – is the normalization component, $t$, $s$ – time scale parameter and $\tau$ – time position parameters. Normalization ensures that the wavelet transforms at each scale are comparable to each other and to the transforms of other time series. The wavelet function at each scale is normalized to have unit energy to allow for this comparison (Torrence and Compo 19998). By projecting a time series on a wavelet function $\psi_0(\eta)$, which must be time–frequency space localized and have zero mean, the decomposition enables information from the local neighbourhood to be obtained. For this purpose, the Morlet wavelet is frequently used (Ng & Chan, 2012).

The Morlet wavelet function can be expressed as:

$$\psi_0(\gamma) = \frac{1}{\sqrt[4]{\pi}}e^{i\eta\omega_0}.\frac{1}{\sqrt{e^{\eta^2}}} \tag{2}$$

where $\frac{1}{\sqrt[4]{\pi}}$ – The normalization term η – Time and dimensionless central frequency parameters $\omega_0$ – Angular frequency (in radians per unit time) from the mother wavelet, the time series could be disintegrated as follows:

$$F_x(s,\tau) = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{+\infty} f(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{3}$$

where * is a complex conjugate. The variance of the above process will be as follows:

$$x^2 = \frac{1}{C_\psi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} F_x(s,\tau)^2 dt\frac{ds}{s^2} \tag{4}$$

In the time–frequency domain, wavelet coherence can be thought of as a localized correlation. A wavelet coherence around 1 indicates a stronger resemblance between the two variables, akin to the classical correlation measure, but a value of zero (0) indicates no association (Cărăuşu et al., 2018). The Wavelet Power Spectrum $|F_x|^2$ of a signal represents the energy density of the signal in the frequency-time domain. Given any two wavelet transforms ($F_x andF_y$) one of the best ways to compare the two wavelets is the Cross-Wavelet Power (CWP) represented by:

$$F_x = |F_xF_y| \tag{5}$$

It shows the local covariance of the two signals at different scales and frequencies. The CWP is a correlation measure that employs cross-wavelet coherence to acquire a better understanding of a pair of time-varying bivariate data series relationships. Just as the Fourier coherency transform, wavelet theory also makes use of wavelet coherency. The following equation is an expression of the bivariate wavelet coherence;

$$R_t{}^2 = \frac{|M(F_t{}^{xy})(m)|^2}{M(m^{-1}|F_t{}^x(m)|^2).M(m^{-1}|F_t{}^y(m)|^2)} \tag{6}$$

where M depicts the smoothing operator. A wavelet coherence could be considered as a localized correlation in the time–frequency domain. The wavelet coherence is calculated as a modulus for the wavelet cross-spectrum, which is standardized for each wavelet spectrum. This is important because it emphasizes the frequency and time interval of a strong connection between two signals. (Amewu et al., 2022; Armah et al., 2022). According to Madaleno & Pinho, (2012), the Wavelet Phase Difference Function (WPD) shows a lead-lag connection between two given signals expressed as follows:

$$\theta_{xy} = tan^{-1}\left\{\frac{I(F_t^{xy})}{R(F_t^{xy})}\right\}, \theta_{xy}\in[-\pi,\pi] \tag{7}$$

The absolute value of $\theta_{xy}$ is a measure of coherence. For instance, a phase greater than $\pi/2$ shows that the series in question are out of phase and one less than $\pi/2$ shows that the series is in phase. We can use not only the magnitude of the phase but also the direction in which the variables within the phase move. The lead-lag relationship between the two series can be determined by studying the phase direction.

### 3.2. Partial wavelet coherence (PWC)

The influence of the time series $z(t)$, the control variable (world COVID-19 media coverage) which could influence the co-movement between equity and exchange rate during the pandemic period, could be removed with the application of wavelets(Wu et al., 2020). Following (Ng & Chan, 2012) we define PWC as follows:

$$R_p^2(x,y,z) = \frac{|R(x,y) - R(x,z).R(x,y)^*|^2}{[1-R(x,z)]^2[1-R(x,z)]^2} \tag{8}$$

where 0â¦¤$R_p^2(x,y,z)$â¦¤1 follows the interpretation for $R_p^2(x,y,z)$ shows the partial wavelet coherence between two variables: $x$ and $y$ with $z$ acting as a control variable.

### 3.3. Volatility connectedness approach

We employ the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) method postulated by Gabauer, (2020). This method was developed as a replacement for the connectedness approach of Diebold & Yilmaz, (2014)) and is used to measure the volatility transmission mechanisms between the variables. The DCC-GARCH method primarily emphasizes the relationship between the shock in variable $i$ and the conditional volatility of variable $j$, and evaluates the extent of co-movement or correlation between variables, taking into account volatility clustering and time-varying correlations (Kyei et al., 2024). The motivation for adopting this method is based on the shared objective of capturing the connections or correlation between stock exchange rate return and the international market.

### 3.4. Volatility decomposition method

We employed Hodrick & Prescott, (1997) to decompose volatility into trend and cycle parts following Danielsson et al., (2018) as follows:

$$volatility_{i,t}^{high} = \begin{cases} \sigma_{i,t}, \tau_{i,t}\sigma_{i,t} \geq \tau_{i,t} \\ 0, otherwise \end{cases} \tag{9}$$

$$volatility_{i,t}^{low} = \begin{cases} \sigma_{i,t}, \tau_{i,t}\sigma_{i,t} \geq \tau_{i,t} \\ 0, otherwise \end{cases} \tag{10}$$

### 3.5. DCC-GARCH connectedness approach

To examine the time-varying conditional volatility, first, we implemented the two-step approach of DCC-GARCH postulated by Engle, (2002) and then applied the connectedness approach by Gabauer (2020). The model for GRACH(1,1) is estimated as follows:

$$y_t = u_t + \varepsilon_t\varepsilon_t|F_{t-1}\ N(0,S_t) \tag{11}$$

$$\varepsilon = H_t^{1/2}u_tu_t\ N(0,I) \tag{12}$$

$$S_t = D_tR_tD_t$$

where $F_{t-1}$ describe all information available up to t-1. $y_t, u_t, \varepsilon_t$ are $KX1$ dimensional vectors depicting the time series, conditional mean, error term and standard error.$S_t$, $D_t$, and$R_t$ = diag($h_{11t}^{0.5}\cdots..h_{nnt}^{0.5}$) are $SXS$ dimensional matrices, describing the dynamic correlation between time-varying conditional variance–covariance matrices and time-varying conditional variance. At the initial stage, the $D_t$ is established by estimating a Bollerslev, (1986) GARCH model for each individual series. Following Hansen and Lunde Hansen & Lunde, (2005), it is assumed that there is only one shock and one persistency parameter (Gabauer 2020).

$$h_{ii,t} = \omega + \alpha \epsilon^2_{i,t-1} + \beta h_{ii,t} \tag{13}$$

The dynamic conditional correlation is computed as follows:

$$R_t = diag\left(q_{iit}^{-0.5}, \cdots\cdots q_{nnt}^{-0.5}.\right) Q_t diag\left(q_{iit}^{-0.5}, \cdots\cdots q_{nnt}^{-0.5}.\right) \tag{14}$$

$$Q_t = (1 - s - y)\check{Q} + s\dot{u}_{t-1}u'_{t-1} + yQ_{t-1}$$

where $Q_t$ and $\check{Q}$ are $KXK$ dimensional positive-definite which depicts conditional and unconditional standardized residual variance–covariance matrices while s($\alpha$) and y($\beta$) are nonnegative shocks and persistency parameters that satisfy $s + y + 1(\alpha + \beta \leq 1)$.

Following the work of Gabauer (2020), we then compute GFEVD as follows:

$$\widehat{\varnothing}^g_{ij,t}(j) = \frac{\sum_{t=1}^{j-1} \Psi^{2,g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{j-1} \Psi^{2,g}_{ij,t}} \tag{15}$$

With $\sum_{j=1}^{N} \widehat{\varnothing}^g_{ij,t}(j) = 1$ and $\sum_{j=1}^{N} \widehat{\varnothing}^g_{ij,t}(j) = N$, using the GFEVD the total connectedness index is as follows:

$$C^g_{,t}(j) = \frac{\sum_{i,j=1, i \neq j}^{N} \widehat{\varnothing}^g_{ij,t}(j)}{\sum_{j=1}^{N} \widehat{\varnothing}^g_{ij,t}(j)} * 100 \tag{16}$$

$$= \frac{\sum_{i,j=1, i \neq j}^{N} \widehat{\varnothing}^g_{ij,t}(j)}{N} * 100 \tag{17}$$

This connectedness approach shows how the shocks of one variable spillover into the shocks of other variables. Using the GFEVD, the total directional connectedness to each other is as follows:

$$C^g_{,i \to j,t}(j) = \frac{\sum_{i,j=1, i \neq j}^{N} \widehat{\varnothing}^g_{ij,t}(j)}{\sum_{j=1}^{N} \widehat{\varnothing}^g_{ij,t}(j)} * 100 \tag{18}$$

We further determine the directional connectedness from others where *i* receive it from variable *j*. This is defined as follows;

$$C^g_{,i \leftarrow j,t}(j) = \frac{\sum_{i,j=1, i \neq j}^{N} \widehat{\varnothing}^g_{ij,t}(j)}{\sum_{j=1}^{N} \widehat{\varnothing}^g_{ij,t}(j)} * 100 \tag{19}$$

The difference between equation (19) and equation (20) is known as net total directional connectedness; this is defined as follows;

$$C^g_{,i} = C^g_{,i \to j,t}(j) - C^g_{,i \leftarrow j,t}(j) \tag{20}$$

The net total directional connectedness is broken down in order to examine the bidirectional relationship between the variables by computing the net pairwise directional connectedness (NPDC) as follows:

$$NPDC_{ij}(j) = \frac{\widehat{\varnothing}^g_{ji,t}(j) - \widehat{\varnothing}^g_{ij,t}(j)}{T} * 100 \tag{21}$$

## 4. Data and discussion

The data considered in this study are the daily series of the equity indexes and the exchange rate for South Africa, Ghana, Nigeria, Kenya, Egypt, Mauritius and Morroco. Our sample size is based on the top 10 equity markets in Africa for the year 2021.[2] However, due to data availability issues, we only obtained seven countries for our analysis. These countries are representative because they cover the four regional blocks in Africa:- Northern, Western, Eastern and Southern Africa. Implied market volatility indices comprise stock market volatility (VIX), COBOE euro currency ETF volatility index (EVZCLS), CBOE crude oil EFT volatility index (OVXCLS), CBOE gold EFT volatility index (GVZCLS). Using the options prices on the S&P index, VIX is designed to reflect the investor expectation of the equity market. We employed the COBOE euro currency ETF volatility index (EVZCLS) to proxy foreign exchange markets. The EVZCLS is estimated 30-day volatility of the Euro/USD exchange rate by tracking the underlying options mid quotes on the currency share Euro Trust.

We also employed the CBOE crude oil EFT volatility index (OVXCLS) and CBOE gold EFT volatility index (GVZCLS) to proxy the Gold share EFT and Crude oil EFT volatility index. CBOE gold EFT volatility index (GVZCLS) and CBOE crude oil EFT volatility index(OVXCLS) are the measured expected 30-day volatility option mid-quotes values for Gold and Oil. The data set for exchange rate and equity indices were sourced from datastream, world media coverage indices were sourced from Ravenpack and EVZCLS, OVXCLS, GVZCLS and VIX were retrieved from Federal Reverse of Bank of St. Louis. Our data set spans from January 2018 to December 31, 2021. The price level data were dollars denominated for the case of uniformity. We argue that international sentiment may have an impact on the financial market rather than local sentiment; therefore we employ world COVID-19 media coverage indicators as a control variable in partial wavelet estimation. We use log returns computed as $R_t = [In(p_t) - In(p_{t-1})] * 100$.

### 4.1. Descriptive statistics

Table 1A reports statistical moments along with the normality test, unit root test, and autocorrelation. The mean value of equity returns for South Africa and Nigeria is negative whereas Morocco, Mauritius Ghana, and Egypt show positive. Exchange rates for Ghana and South Africa exhibit negative returns while Morocco, Nigeria, Kenya, Egypt and Mauritius show positive. All the series exhibit excess kurtosis and their skewness shows that the distribution of all the variables appears to be non-normal. This supports the argument posited by Jarque & Bera, (1980), that in normality tests, all series are significantly non-normally distributed. In addition, ERS statistics indicate that all the series are I(0) except for GHA, EGPT, NIG, KEN, MAU, and MORO for which the series are I(I). The presence of serial correlation based on 20 lags confirmed by Ljung-Box statistics (Q, Q2) evidences the possibility of serial correlation in residuals (Q (20)) and square residual ($Q^2$(20)) for all series.

### 4.2. Time-frequency analysis

In this section, we first analyze the interdependence between equity and currency volatility using bivariate wavelet coherence. To determine or justify whether the world coverage of COVID-19 media has an impact on the interdependence between the volatility of equity and currencies, we performed a partial wavelet analysis (Fig. 1B right panel) for the COVID-19 subsample period by controlling the COVID-19 media coverage. The bivariate wavelet coherence (Fig. 1B, left panel) is estimated using the full sample. This helps to ascertain the difference in co-movement and establish whether the interdependence between equity and currency markets was driven by investor sentiment as a result of world media coverage.

The wavelet coherence takes into account individual power

[2] https://africa.businessinsider.com/local/markets/10-best-performing-african-stock-markets-in-2021/cmfg5sg.

**Table 1A**
Descriptive statistics.

| | countries | Mean | Skewness | Ex. Kurtosis | JB | ERS | Q(10) | Q2(10) |
|---|---|---|---|---|---|---|---|---|
| Stocks returns | | | | | | | | |
| GHA | Ghana | 0.223 | 0.133* | −0.771*** | 28.940*** | −1.024 | 5697.896*** | 5697.409*** |
| EGPT | Egypt | 1.034 | −0.189** | −1.066*** | 55.640*** | −1.483 | 5448.044*** | 5448.713*** |
| NIG | Nigeria | −0.003 | −0.509*** | −0.748*** | 69.372*** | −0.952 | 5644.736*** | 5645.961*** |
| KEN | Kenya | 0.000 | 0.330*** | −1.194*** | 81.113*** | −1.024 | 5605.372*** | 5603.171*** |
| MAU | Mauritius | 0.225 | −0.039 | −0.770*** | 26.076*** | −1.104 | 5384.836*** | 5386.462*** |
| SAF | South Africa | −1.240 | 0.126* | 0.486*** | 13.018*** | −2.442** | 5313.564*** | 5318.613*** |
| MORO | Morocco | 1.063 | −0.407*** | −0.092 | 29.178*** | −1.281 | 5504.415*** | 5506.204*** |
| Exchange rate | | | | | | | | |
| NIGX | Nigeria | 1.920 | 0.420*** | −1.590*** | 140.820*** | −1.465 | 5464.836*** | 5465.452*** |
| GHAX | Ghana | −0.002 | −5.418*** | 69.347*** | 214505.303*** | −3.462*** | 2609.778*** | 4368.232*** |
| KENX | Kenya | 0.005 | −18.004*** | 329.128*** | 4773115.073*** | −11.771*** | 597.112*** | 684.504*** |
| SAFX | South Africa | −0.004 | 0.039 | 0.452*** | 9.159*** | −1.763* | 5492.408*** | 5491.600*** |
| EGPTX | Egypt | 0.001 | 0.528*** | −1.412*** | 135.252*** | −1.204 | 5522.660*** | 5523.542*** |
| MAUX | Mauritius | 0.023 | 0.147* | −1.214*** | 67.906*** | −1.26 | 5486.045*** | 5485.974*** |
| MORX | Morocco | 0.967 | −16.687*** | 297.266*** | 3896144.741*** | −11.316*** | 295.841*** | 628.877*** |
| Implied volatility | | | | | | | | |
| VIX | | 0.006 | −1.109*** | 9.948*** | 4523.062*** | −14.715*** | 22.658*** | 247.796*** |
| EVZCLS | | −0.002 | −4.625*** | 71.599*** | 226941.378*** | −0.688 | 22.387*** | 0.728 |
| OVXCLS | | −0.002 | 1.359*** | 26.811*** | 31620.210*** | −8.069*** | 39.027*** | 96.970*** |
| GVZCLS | | −0.001 | 0.226*** | 9.604*** | 4025.270*** | −6.042*** | 10.693** | 143.788*** |
| COVID.19.MCI | | 1.743 | −0.530*** | −0.716*** | 71.201*** | −0.689 | 4801.528*** | 4836.043*** |

Notes (***), (**) and (*) denote significance at 1%,5%, and 10% significance level, respectively; Kurtosis test; Anscombe & Glynn, (1983) JB; Jarque & Bera, (1980) normality test; ERS;(Elliott et al., 1996, Unit root test; $Q(20)$ and $Q^2(20)$ shows the Ljung-Box p-value for residuals and square residualin with the lags 10 and 20 respectively (Fisher & Gallagher, 2012).

differences and provides the combined characteristics of different signals (Roesch. & Schmidbauer, 2014). These are given in Fig. 2a to 2n of the heat map. In the heatmap, the area of interest is at 5 % significance and lies in the zone of influence within the white contours with directional arrows. For instance, when the arrows point in the right direction, it means that the two series are in phase and when they point left, it means that they are out of phase (anti-phase). For arrows pointing right and up, they indicate that the first variable is leading (thus the second variable is lagging) While arrows that point right and down indicate that the first variable is lagging (that is, the second variable is leading).

Alternatively, arrows that point left and up indicate that the second variable is leading, while those that point left and down indicate that the second variable is lagging. The red colour in the white contour in both panels (left and right panel) shows a strong co-movement between the two signals at both end and beginning. The red colour in the white contour at the top and down of the heatmap indicates strong co-movement at high and low frequencies. The results outside the COI are insignificant since they are beyond the 95 % confidence level. The horizontal axis shows the time, while the vertical axis gives a frequency band that varies from low to high frequency. The colour bar displays the degree of coherence as it moves from blue (weak coherence) to red (strong coherence).

The co-movement of equity and exchange rate are presented in Fig. 2a-2n, which contains plots of bivariate wavelet coherence (left panel) and partial wavelet coherence (right panel). These plots are presented to reveal the extent of co-movement between equity and exchange rates when world COVID-19 media coverage is treated as a covariate, excluding the effect of country-specific COVID-19 media coverage. We examine the co-movement between the equity nexus exchange rate for countries specific with their corresponding partial wavelets when the covariate (world COVID-19) media coverage is used in order to ascertain the difference in the co-movement. From Fig. 2 which reveals the scalogram for the bivariate (left panel) between the equity market and exchange rate for Ghana (GHA-GHAX), we observe that at the frequency band of 2–16 days between 2018 to the early part of 2020, the positioning of arrows (←) signify that the variables are out of phase $\left(-\frac{\pi}{2}, -\pi\right)$ However, at the high-frequency band of 32–256 daily in the same period, the co-movement between the equity market and exchange rate exhibited antiphase $\left(-\frac{\pi}{2}, -\pi\right)$ relationship with a slight indication that the equity market is driven by exchange rate volatility which saw a full manifestation in 2019 and 2020 with (↖) and (↙) positioning the arrow at high frequency (128–256) daily. Similar dynamics were spotted in the case of Egypt(EGPT-EGPTX) between late 2019 and 2020.

We also notice that at the highest frequency band of 128–256 for Kenya(KEN-KENX), and Nigeria(NIG-NIGX), the co-movement between equity and exchange rate are out of phase $\left(-\frac{\pi}{2}, -\pi\right)$ between the period of 2018-late 2020, however, at the medium frequency band, there is a mixture of upward (↖), (↗) and downward (↙)(↘) highlighting the potential for equity market and exchange rate drive each other. This shows that the exchange rate and the dynamics of the equity market are interdependent and unidirectional in the medium term between the period of 2018 and the early part of 2020.

From the scalogram, we observe that both the right and left arrows downward (↙)(↘) suggest that stock return plays a dominant role in the exchange rate volatility. This implies that an increase in stock prices drives attracting foreign investors which induces excess demand for local currency and hence exacerbates currency depreciation in the currency market. This observation is consistent with the work of (Agyei et al., 2022; Amewu et al., 2022), and also consistent with portfolio balance theory (Frankel, 1992) which asserted that the volatility of stock prices in the economy may influence exchange rates through the inflow and outflow of foreign capital. Turning back to Ghana, Nigeria, and Kenya, we observe that the right-pointing arrow (→) implies that the series is in phase $\left(0, \frac{\pi}{2}, \right)$. The frequency band of 2–32 daily suggests that there is a co-movement and bidirectional causality between stock returns and exchange rates during the pandemic period.

However, for South Africa, Morocco, Mauritius and Egypt we notice that there are few upward, right, and left pointing arrows (↗) (↖) suggest that the equity market in these countries drives the currency market during the pandemic period at the lower frequency band. This finding indicates the co-movement between exchange rate and stock

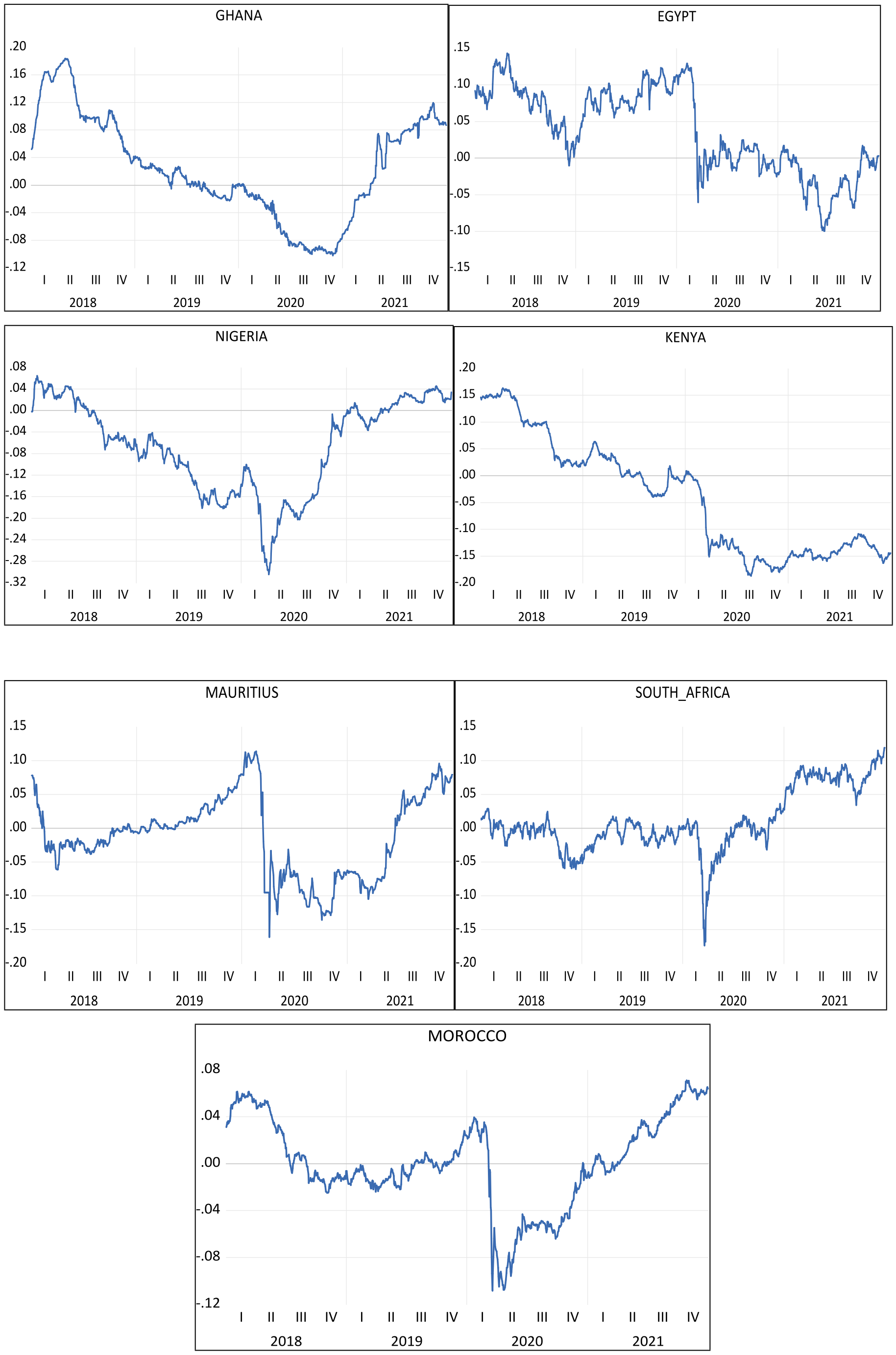



**Fig. 1B.** Dynamic conditional correlation between stock returns and exchange returns.

market returns varies across time and frequency and these are similar to the findings of other studies (Agyei et al., 2022; Amewu et al., 2022; Loh, 2013). There is a consensus that world COVID-19 media coverages are usually associated with fear and panic in the market (Umar et al., 2021b; Dragomirescu-Gaina & Philippas, 2022; Bossman, Teplova, et al., 2022).

The complex co-movement dynamics between world media coverage and co-movement between equity and currency markets stress the pivotal role of global factors in driving the financial system in emerging economies (Dragomirescu-Gaina & Philippas, 2022). We isolate the world's COVID-19 media coverage from the bivariate interaction through partial wavelet coherence. The disparity in bivariate wavelet coherence and partial wavelet coherence is a statistical test of the impact of world COVID-19 media coverage on the co-movement of equity and exchange rate returns. We present the partial wavelet coherence in the right panel of Fig. 2. From the scalogram, the partial wavelet plots do not show phase differences (Wu et al., 2020), and no correspondence of COI locations shows the influence of control variables (world COVID-19 media coverage) in the partial wavelet.

The essence of partial wavelet is to investigate whether world COVID-19 media coverage drives the co-movement between equity and exchange rate returns in Africa. From the plot, we observe that the effect of world COVID-19 media coverage has a significant impact on different scales and frequencies on the comovement between equity and exchange rate during COVID-19 in all pairs except South Africa(SAF-SAFX) and Egypt (EGPT-EGPTX) which indicate that world COVID-19 media coverage drives a change in the lead-lag interrelationship between

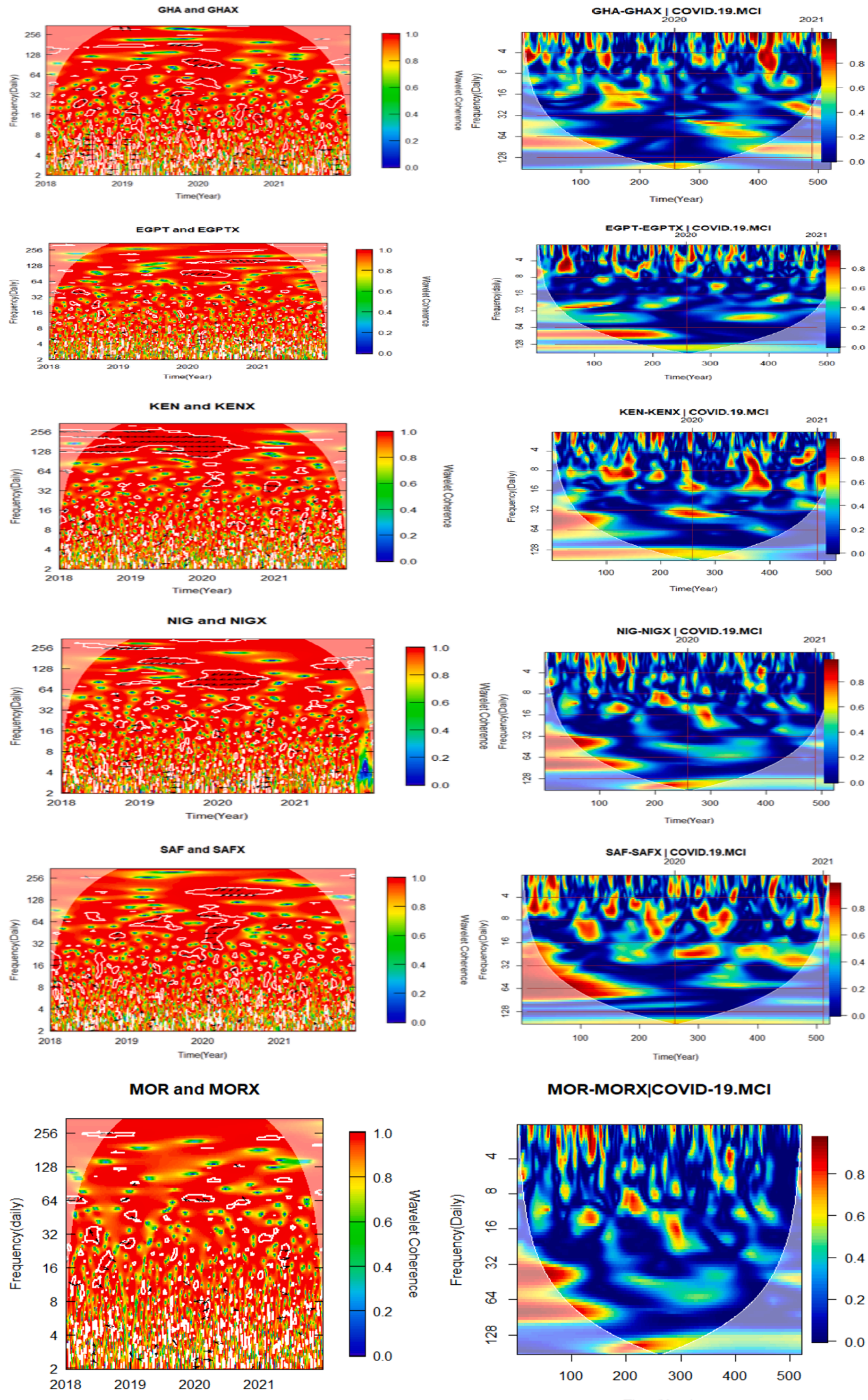



**Fig. 2.** (a-n): Bivariate coherence (left panel) and partial wavelet coherence (right panel) for world COVID-19 media coverage. Details descriptions of the figures are in the text.

equity and exchange returns during COVID-19. This finding collaborates with the existing literature that reveals time and frequency dynamics between world media coverage and financial assets (Umar et al., 2021b; Bossman, Teplova, et al., 2022).

To examine dynamic linkage and volatility spillover, we use the DCC-GARCH postulated by Engle, (2002). DCC GRACH evaluates the extent of co-movement or correlation between variables, taking into account volatility clustering and time-varying correlations. Then we conduct the BEKK GARCH model postulated by Engle & Kroner, (1995) to capture volatility spillover. From Fig. 2 we find a negative dynamic correlation between stock and exchange rate returns during the COVID-19-induced crisis for all the markets except Egypt and Kenya which show a positive relationship towards the latter part of 2021. The findings imply that the uncertainty surrounding the COVID-19 pandemic led to a decline in domestic stock returns. This caused investors to withdraw their investments from domestic markets, resulting in increased capital outflows and upward pressure on exchange rates (Rai & Garg, 2022). Moreover, our research suggests that the connection between stock and exchange rate returns grew stronger as the pandemic and associated lockdowns progressed, as evidenced by a sudden increase in the 1st and 2nd quarters of 2020. The findings of the DCC-GARCH confirm the result of wavelet coherence. However, the DCC-GARCH findings do not offer substantial information regarding the shock and volatility spillovers between the nexus hence we investigate the existence of substantial spillovers between the two returns using the BEKK-GARCH model.

Table 1b reports BERKK GARCH (1,1)[3] results. From the findings reported, we find that the ARCH effect $(a_{11})$ are significant except for Nigeria and South Africa. The effect of GARCH $(b_{11})$ is significant for all markets indicating that each market experiences its own shocks. This implies that each market is impacted by its own shocks. The off-diagonal $(a_{12})$ and $(a_{21})$ captures the cross-market effect shocks. The results show that both $(a_{12})$ and $(a_{21})$ are significant for the countries except Nigeria. This implies that there is evidence of bidirectional shock spillover between stock returns and exchange rates for Ghana, Mauritius, Morocco Egypt Kenya and Unidirectional for South Africa and Nigeria. Our findings indicate that there is a considerable risk transfer between stock and exchange rate returns. Moreover, our BEKK-GARCH model aligns with the DCC-GARCH model and wavelet coherence in suggesting that the negative dynamic correlation between stock returns and exchange rate returns intensified during the uncertainties period of COVID-19. These findings are in line with the work of Rai & Garg, (2022), Amewu et al., (2022) and He et al. (2021a,b).

### 4.3. Dynamic volatility spillover

Having established the co-movement between equity and equity markets, it is necessary to examine further to what extent the African markets are connected and how likely they are to converge as a result of financial market integration. We employ the DCC-GARCH model to analyse the volatility connectedness between the African equity market and the international market. The average dynamic under DCC-GARCH connectedness provided a dynamic perspective of high and low volatility as presented in Tables 2 & 3 respectively. The main diagonal of the matrix shows information about the contribution of one-day lag to market shock *to* their own forecast error variations. The off-diagonal column "To" and the row "From" describes the entire directional connectedness of all variables in the system from *i* and from all others to, *i,* respectively. The row "net" is the total sum of the net pairwise directional spillover expressed in positive and negative values to represent the net transmitter.

The results reported in Table 2a show an average of the total connectedness index (TCI) value of 25.31, implying that 25.31 % of the volatility in one asset spillover to another asset. However, in the high volatility, we observed that the TCI value is 59.10 % implying the African equity market is highly connected with the international market. The highest(lowest) spillover effect for low volatility in the African equity market is observed from Mauritius (MAU) to Nigeria (NIG) which is 9.52 to −7.72 for low volatility. However, in the high volatility, we observed that Egypt (EGPT) and Morocco (MOR) are net transmitters of spillover. From the results in Table 2a and Table 2b, it is evident from the pairwise connectedness values that the volatility spillover effect from the international market (VIX) is substantial for both low and high volatility, indicating that significant fluctuations in the implied volatility play a significant role in the volatility of Africa equity and currency markets. In the low volatility VIX, EVZCLS, OVXCLS and GVZCLS have the highest TO. The NET values show that implied market volatilities are the main volatility transmitter to the African equity market in the case of low volatility except for Mauritius(MAU) Morocco(MOR) and South Africa(SAF) which show a positive value of NET, implying that equity market for these countries are net transmitter of risk whereas Egypt (EGPT) Ghana(GHA) Kenya(KEN) are the net receivers of shocks. In Table 3a&Table 3b we also observed that the TCI for high volatility is stronger than the TCI in the low volatility in the case of currency market and Implied volatility. The sudden surge in dynamic total connectedness reflects the severe impact of the COVID-19 pandemic when asset markets experienced significant increases in volatility due to the uncertainty caused by the virus in the global economy. As already opined by Antonakakis et al. (2023), Umar and Bossman, (2023) and Armah and Amewu, (2024), events such as COVID-19 tend to create a stronger linkage and this mostly occurred at high volatility. The surge in TCI at the high volatility signals early warning ability for future market risk and better information in real-time. Our findings corroborate with Xiang & Borjigin, (2024) who did similar work in the commodity market. In the low volatility table (see Table 3A) we notice that the currency market exhibits the net transmitter of spillover except South Africa (SAFX) and Mauritius (MAUX), and the larger net transmitter of spillover is OVXCLS. This phenomenon implies that the African currency market is sensitive to the changes in uncertainty for oil prices. The tendency for investors to follow the crowd can create market panic and fear, leading to substantial declines in the African currencies and this undermines investor confidence. However, in the higher volatility Ghana (GHAX), South Africa (SAFX) and Egypt (EGPX) are the net recipients of spillover.

To examine the magnitude and direction of the high and low volatility spillover effect between the African equity market and market volatility, we plot high and low volatility spillover networks based on the estimated spillover matrices as shown in Fig. 2a&2b and Fig. 3aa&Fig. 3b. We split the data into pre-COVID-19(January 2018 to March 30, 2020) and COVID-19 periods(March 31, 2020 to December 31, 2021) in order to comprehend the volatility spillover between the nexus. From the network analysis, we observe that the direction and magnitude of spillover differ significantly between the high and low for both networks. For instance, in Fig. 3a we find that VIX and OVXCLS are the main transmitters of spillover in high and low volatility and GHA, MAU, MOR KEN are the net transmitter of risk in the low volatility whereas SAF, NIG and EGPT are the net recipients. In Fig. 3a of panel B SAF, MOR, and MAU are the net transmitter of spillover in the high volatility whereas NIG, KEN, GHA, and EGPT are net recipients. This suggests that giving a particular asset assumes distinct functions in high and low volatility networks, thereby validating the disparities between the two types of networks as shown in Fig. 3a&Fig. 3bb. During the period of COVID-19 we observe in the high and low volatility that SAF, NIG, EGPT, MAU are the largest net recipients of a spillover effect from OVXCLS, GVZCLS and VIX whereas KEN GHA, MOR are the net transmitters. However, in panels A and B of Fig. 3a the network analysis shows that OVXCL is indeed the net recipient of shock before COVID-19. This comes as a surprise that OVXCL does not transmit volatility spillover shocks before and during COVID-19 despite evidence suggesting the opposite (Bouri et al., 2023; Kang et al., 2023). Nevertheless, the oil implied volatility's net receiving character can be explained by the increased integration of oil into the financial system since the Global Financial Crisis of 2009 (Antonakakis et al., 2023). This integration makes the oil market more susceptible to financial market fluctuations across the world, providing further evidence of the higher financialization of the oil market (Creti & Nguyen, 2015; Zhang, 2017). From the network analysis, we observe that the difference in the high and low volatility spillover in terms of risk transmitter and risk receivers offer a potential advantage for investors and to identify the risk accumulation and risk outbreak as well as the corresponding contagion mechanism for investment strategies.

[3] we estimated BERKK GARCH as follows: $Q_t = CC' + A_{\epsilon t-1 \epsilon'_{t-1}} A' + BQ_{t-1}B'$. The conditional covariance matrix, denoted as $Q_t$ includes diagonal elements of matrix A and B that represent the ARCH and GARCH effects, respectively. Meanwhile, the off-diagonal elements of matrix A and matrix B capture the shock spillover and volatility spillover between stock returns and exchange rate returns, respectively.

**Table 1B**
BEKK-GARCH(1,1) model- Volatility spillover between Exchange rate and stock returns for African markets.

| | Morocco | Ghana | Nigeria | Kenya | Mauritius | South Africa | Egypt |
|---|---|---|---|---|---|---|---|
| $\mu_1$ | 2.05E-06 | 3.395 | 2.886 | 3.449 | 3.1287 | 0.053 | 1.0035 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | 0.072 | (0.000)*** |
| $\mu_2$ | 1.90E-07 | −0.003 | 0.081 | −0.001 | 0.0027 | −0.045 | 1.9776 |
| | −0.1024 | (0.000)*** | (0.000)*** | 0.166 | 0.8896 | 0.071 | (0.000)*** |
| $c_{11}$ | 4.30E-07 | 1.321 | 2.742 | 1.851 | 1.634 | 1.164 | −0.173 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| $c_{12}$ | 1.2522 | −0.164 | −0.073 | 0.036 | −0.0117 | 0.001 | 0.0587 |
| | (0.000)*** | (0.000)*** | (0.000)*** | −0.272 | −0.1707 | −0.763 | (0.000)*** |
| $c_{22}$ | 1.2639 | 1.243 | −0.245 | −0.261 | 0.8352 | 0.001 | 0.9678 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | 0.000)*** | (0.000)** | (0.000)*** |
| $a_{11}$ | 0.619 | −0.09 | −0.109 | −0.123 | 0.8857 | 0.000 | 0.9567 |
| | (0.000)*** | (0.000)*** | 0.292 | (0.000)*** | (0.000)*** | 0.235 | (0.000)*** |
| $a_{12}$ | −0.604 | −0.792 | 0.180 | −1.279 | 0.574 | −0.112 | 0.228 |
| | (0.000)*** | (0.000)*** | 0.039 | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| $a_{12}$ | −0.067 | 0.786 | −0.891 | 1.404 | 0.473 | −0.304 | −0.2978 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| $a_{22}$ | 0.097 | 0.827 | 0.008 | 1.406 | −0.345 | −0.183 | 0.9678 |
| | −0.102 | (0.000)*** | 0.734 | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| $b_{11}$ | 0.643 | 0.743 | 0.463 | 0.21 | 0.8352 | 0.933 | 0.9567 |
| | (0.000)** | 0.000*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| $b_{12}$ | 1.252 | 0.597 | 0.994 | 0.206 | 0.8857 | 0.482 | 0.2284 |
| | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** | (0.000)*** |
| $b_{21}$ | 1.264 | 0.000 | 0.000 | 1.404 | 0.574 | 0.591 | 0.298 |
| | (0.000)*** | (0.000)*** | (0.020)*** | (0.000)*** | (0.000)*** | 0.0000 | (0.000)*** |
| $b_{22}$ | 0.619 | −0.009 | −0.001 | 1.406 | 0.473 | 0.042 | 0.000 |
| | (0.000)*** | (0.000)*** | 0.292 | (0.000)*** | (0.000)*** | 0.616 | (0.000)*** |

Note: The values in the parenthesis are p-values. (***), (**),(*) indicate statistical significance level at 1%, 5% and 10%.

**Table 2A**
Average dynamic connectedness of implied volatility and equity market(low volatility).

| | EGPT | GHA | KEN | NIG | SAF | MOR | MAU | VIX | EVZCLS | OVXCLS | GVZCLS | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EGPT | 73.05 | 1.2 | 1.68 | 0.91 | 2.53 | 7.05 | 3.71 | 0.85 | 0.56 | 3.98 | 4.47 | 26.95 |
| GHA | 1.94 | 86.18 | 1.15 | 0.7 | 1.19 | 1.16 | 1.64 | 4.08 | 0.91 | 0.51 | 0.54 | 13.82 |
| KEN | 2.26 | 1.05 | 86.41 | 0.76 | 1.27 | 2.12 | 2.66 | 0.83 | 0.56 | 0.99 | 1.09 | 13.59 |
| NIG | 1.73 | 1.21 | 0.81 | 80.34 | 3.44 | 1.69 | 3.38 | 1.21 | 1.32 | 2.43 | 2.43 | 19.66 |
| SAF | 2.05 | 0.58 | 0.9 | 1.96 | 80.11 | 2.81 | 2.38 | 0.28 | 1.23 | 3.65 | 4.06 | 19.89 |
| MOR | 6.49 | 0.95 | 1.38 | 2.18 | 2.79 | 70.84 | 3.41 | 0.98 | 3.53 | 3.53 | 3.91 | 29.16 |
| MAU | 1.69 | 1.03 | 0.95 | 1.81 | 2.09 | 2.45 | 82.7 | 1.82 | 0.59 | 3.07 | 1.81 | 17.3 |
| VIX | 0.61 | 2.45 | 0.45 | 0.93 | 1.47 | 0.57 | 2.22 | 89.03 | 0.94 | 0.73 | 0.59 | 10.97 |
| EVZCLS | 1.59 | 1.29 | 1.06 | 0.89 | 1.02 | 4.81 | 1.83 | 1.16 | 76.41 | 3.9 | 6.04 | 23.59 |
| OVXCLS | 3.5 | 0.66 | 0.58 | 0.78 | 2.37 | 2.82 | 3.26 | 0.49 | 2.75 | 62.06 | 20.76 | 37.94 |
| GVZCLS | 4.28 | 0.53 | 1.19 | 0.68 | 2.55 | 3.71 | 2.34 | 0.51 | 3.96 | 20.48 | 59.76 | 40.24 |
| TO | 26.15 | 10.93 | 10.15 | 11.6 | 20.73 | 29.19 | 26.83 | 12.21 | 16.36 | 43.25 | 45.7 | 253.11 |
| Inc.Own | 99.21 | 97.11 | 96.56 | 91.94 | 100.84 | 100.03 | 109.52 | 101.24 | 92.77 | 105.31 | 105.47 | TCI |
| NET | −0.79 | −2.89 | −3.44 | −8.06 | 0.84 | 0.03 | 9.52 | 1.24 | −7.23 | 5.31 | 5.47 | 25.31 |

Notes; Results are based on DCC GARCH (1,1) model and 100-step-ahead generalized forecast error variance decomposition. Inc. Own refers to the contribution including own. TCI denotes total connectedness index.

**Table 2B**
Average dynamic connectedness of implied volatility and equity market(High volatility).

| | EGPT | GHA | KEN | NIG | SAF | MOR | MAU | VIX | EVZCLS | OVXCLS | GVZCLS | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| EGPT | 5.24 | 0.41 | 5.46 | 8.19 | 7.57 | 11.26 | 6.95 | 7.84 | 0.41 | 0.75 | 0.93 | 49.76 |
| GHA | 6.58 | 71.12 | 6.21 | 1.93 | 1.75 | 2.02 | 2.22 | 2.36 | 1.37 | 2.33 | 2.12 | 28.88 |
| KEN | 18.11 | 3.87 | 41.3 | 9.57 | 4.54 | 8.83 | 5.83 | 4.24 | 0.6 | 1.22 | 1.9 | 58.7 |
| NIG | 9.7 | 0.73 | 11.21 | 24.98 | 14.86 | 14.22 | 9.76 | 13.03 | 0.19 | 0.51 | 0.81 | 75.02 |
| SAF | 7.51 | 1.01 | 3.86 | 15.12 | 24.6 | 13.74 | 14.57 | 17.77 | 0.23 | 0.67 | 0.91 | 75.4 |
| MOR | 10.69 | 0.76 | 8.24 | 14.52 | 12.99 | 21.97 | 15.58 | 14.2 | 0.14 | 0.39 | 0.51 | 78.03 |
| MAU | 8.38 | 1.02 | 8.3 | 11.96 | 13.11 | 17.26 | 23.4 | 14.68 | 0.18 | 0.6 | 1.09 | 76.6 |
| VIX | 10.55 | 3.23 | 5.88 | 11.55 | 14.74 | 12.58 | 11.93 | 27.71 | 0.22 | 0.72 | 0.89 | 72.29 |
| EVZCLS | 1.1 | 1.69 | 1.36 | 0.46 | 0.59 | 0.52 | 0.47 | 0.5 | 82.4 | 4.18 | 6.73 | 17.6 |
| OVXCLS | 3.21 | 1.81 | 2.7 | 1.07 | 1.31 | 1.25 | 1.14 | 1.28 | 3.18 | 73.34 | 9.71 | 26.66 |
| GVZCLS | 4.48 | 2.94 | 3.13 | 1.29 | 1.35 | 1.19 | 1.74 | 1.28 | 4.94 | 9.73 | 67.93 | 32.07 |
| TO | 80.31 | 17.49 | 56.33 | 75.68 | 72.8 | 82.86 | 70.19 | 77.18 | 11.48 | 21.09 | 25.6 | 591 |
| Inc.Own | 85.54 | 88.6 | 97.63 | 100.65 | 97.41 | 104.83 | 93.59 | 104.89 | 93.88 | 94.43 | 93.53 | TCI |
| NET | 5.23 | −11.4 | −2.37 | 0.65 | −2.59 | 4.83 | −6.41 | 4.89 | −6.12 | −5.57 | −6.47 | 59.1 |

Notes; Results are based on DCC GARCH (1,1) model and 100-step-ahead generalized forecast error variance decomposition. Inc. Own refers to the contribution including own. TCI denotes total connectedness index.

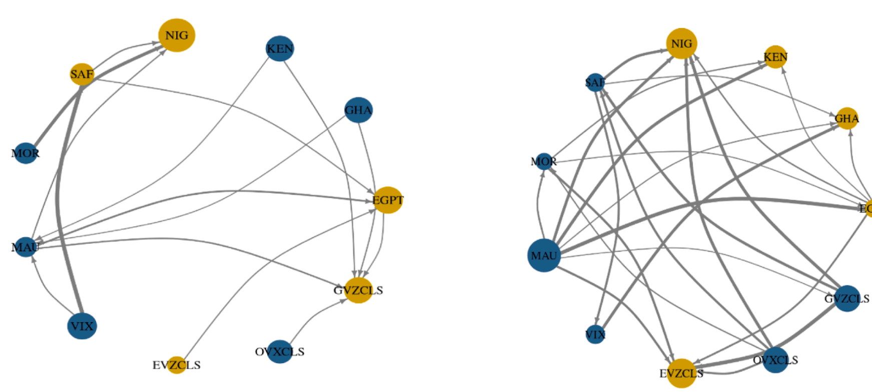
**Table 3A**
Average dynamic connectedness of implied volatility and currency market(low volatility).

| | NIGX | GHAX | KENX | SAFX | EGPTX | MAUX | MORX | VIX | EVZCLS | OVXCLS | GVZCLS | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| NIGX | 55.78 | 8.88 | 3.99 | 5.52 | 9.65 | 3.99 | 1.36 | 3.83 | 2.51 | 2.13 | 2.36 | 44.22 |
| GHAX | 8.69 | 40.25 | 26.23 | 6.71 | 8.16 | 2.66 | 0.99 | 2.62 | 1.12 | 1.55 | 1 | 59.75 |
| KENX | 4.96 | 26.33 | 42.38 | 3.49 | 4.85 | 5.03 | 1.59 | 3.95 | 1.78 | 4.3 | 1.32 | 57.62 |
| SAFX | 5.98 | 6.81 | 3.54 | 57.59 | 12.73 | 3.45 | 1.03 | 3.27 | 1.99 | 2.45 | 1.16 | 42.41 |
| EGPTX | 8.56 | 8.15 | 3.86 | 9.39 | 53.21 | 3.95 | 1.05 | 4.09 | 3.3 | 1.77 | 2.68 | 46.79 |
| MAUX | 4.04 | 2.21 | 4.31 | 3.1 | 4.06 | 59.27 | 6.61 | 4.84 | 2.4 | 7.41 | 1.75 | 40.73 |
| MORX | 0.53 | 0.86 | 1.44 | 0.83 | 0.96 | 3.93 | 84.42 | 1.34 | 0.86 | 4.48 | 0.32 | 15.58 |
| VIX | 4.41 | 2.74 | 3.33 | 3.42 | 6.22 | 6.31 | 4.97 | 63.49 | 1.62 | 2.34 | 1.15 | 36.51 |
| EVZCLS | 3.84 | 2.14 | 3.56 | 2.32 | 5.04 | 3.5 | 1.74 | 3.36 | 62.43 | 6.61 | 5.45 | 37.57 |
| OVXCLS | 2.61 | 1.64 | 2.46 | 1.73 | 2.86 | 2.08 | 2.97 | 2.02 | 3.59 | 69.47 | 8.58 | 30.53 |
| GVZCLS | 4.18 | 2.27 | 2.69 | 1.62 | 4.75 | 2.83 | 0.92 | 2.38 | 5.28 | 10.76 | 62.32 | 37.68 |
| TO | 47.79 | 62.05 | 55.42 | 38.13 | 59.29 | 37.75 | 23.23 | 31.7 | 24.45 | 43.8 | 25.76 | 449.38 |
| Inc.Own | 103.57 | 102.3 | 97.8 | 95.72 | 112.49 | 97.02 | 107.66 | 95.19 | 86.89 | 113.27 | 88.08 | TCI |
| NET | 3.57 | 2.3 | −2.2 | −4.28 | 12.49 | −2.98 | 7.66 | −4.81 | −13.11 | 13.27 | −11.92 | 44.94 |

**Table 3B**
Average dynamic connectedness of implied volatility and currency market (high volatility).

| | NIGX | GHAX | KENX | SAFX | EGPTX | MAUX | MORX | VIX | EVZCLS | OVXCLS | GVZCLS | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| NIGX | 45.2 | 4.61 | 10.61 | 5.75 | 5.22 | 4.84 | 14.07 | 4.09 | 2.19 | 2.46 | 0.96 | 54.8 |
| GHAX | 5.4 | 35.23 | 22 | 3.68 | 2.82 | 10.18 | 4.77 | 5.94 | 1.72 | 3.33 | 4.93 | 64.77 |
| KENX | 6.76 | 9.88 | 53.96 | 7.61 | 1.54 | 3.07 | 10.49 | 1.46 | 1.21 | 1.09 | 2.93 | 46.04 |
| SAFX | 10.14 | 2.68 | 6.52 | 48.75 | 2.73 | 9.33 | 8.05 | 1.97 | 3.8 | 4.37 | 1.66 | 51.25 |
| EGPTX | 16.1 | 7.54 | 8.9 | 7.48 | 31.27 | 8.23 | 8.77 | 4.96 | 2.52 | 3.46 | 0.75 | 68.73 |
| MAUX | 7.52 | 10.73 | 9.82 | 5.22 | 5.66 | 33.06 | 8.8 | 5.37 | 4.6 | 8.26 | 0.97 | 66.94 |
| MORX | 14.15 | 2.98 | 8.27 | 3.29 | 2.24 | 6.52 | 50.72 | 3.06 | 2.41 | 5.67 | 0.68 | 49.28 |
| VIX | 4.95 | 5.09 | 4.32 | 4.15 | 4.14 | 10.33 | 2.83 | 52.71 | 4.01 | 6.04 | 1.42 | 47.29 |
| EVZCLS | 3.34 | 1.31 | 1.99 | 2.18 | 2.06 | 6.02 | 3.45 | 4.72 | 61.67 | 10.19 | 3.06 | 38.33 |
| OVXCLS | 2.69 | 2.02 | 2.18 | 1.71 | 2.34 | 9.05 | 4.74 | 6.1 | 7.3 | 57.91 | 3.96 | 42.09 |
| GVZCLS | 1.84 | 7.58 | 4.64 | 5.48 | 0.95 | 1.31 | 1.55 | 2.95 | 4.82 | 6.91 | 61.98 | 38.02 |
| TO | 72.89 | 54.42 | 79.26 | 46.55 | 29.7 | 68.87 | 67.52 | 40.62 | 34.59 | 51.78 | 21.33 | 567.53 |
| Inc.Own | 118.09 | 89.65 | 133.22 | 95.31 | 60.97 | 101.94 | 118.24 | 93.33 | 96.26 | 109.69 | 83.31 | TCI |
| NET | 18.09 | −10.35 | 33.22 | −4.69 | −39.03 | 1.94 | 18.24 | −6.67 | −3.74 | 9.69 | −16.69 | 56.75 |

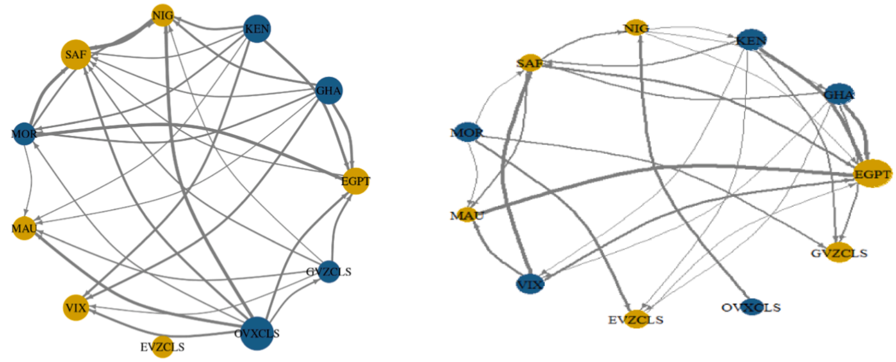
Notes; Results are based on DCC GARCH (1,1) model and 100-step-ahead generalized forecast error variance decomposition. Inc. Own refers to the contribution including own. TCI denotes total connectedness index.




Panel A-Low volatility Panel B-High volatility

**Fig. 3a.** Network plot between Africa equity market and international market-Pre COVID-19. The size of a node in the graph corresponds to the magnitude of the net spillover effects. The hues of blue and yellow signifies that the variable functions as a transmitter or receiver of spillover, with the magnitude of the node indicating the intensity of the spillover impact. There is a positive correlation between the thickness of the edge and the magnitude of the net pairwise spillover effect between the two variables. The node indicated by the arrow symbolizes the recipient of spillover.

Our research validates and extends previous studies in multiple aspects. By employing a static and time-varying examination, we have identified similarities and discrepancies in the relationship between stock exchange rate returns in different time horizons. This underscores the significance of taking into account various investment timeframes when analyzing the behaviour of financial assets (Lee et al., 2023; Armah et al., 2023). While the degree of spillover is relatively lower for the short-term horizon, it significantly increases for long-term horizons, supporting the assertions made by Xiang & Borjigin, (2024) who emphasize the importance of accounting for different time horizons in volatility spillover. The role of VIX as a key transmitter of spillover for the nexus in the high-low volatility across all investment horizons is demonstrated in existing literature, and our study expands these findings to the context of the African market during the COVID-19 pandemic. Although Geng & Guo, (2022), Chen et al., (2022) and Bouri et al., (2023) highlight the role of implied volatility in transmitting




Panel C-Low volatility    Panel D-High volatility

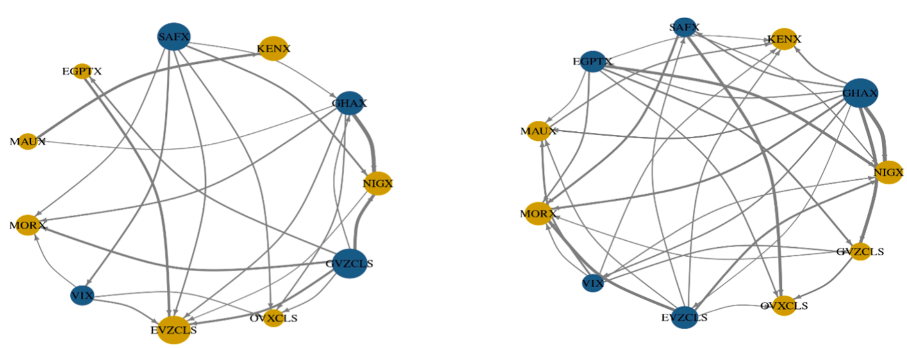
**Fig. 3b.** Network plot for Africa equity market and international market- COVID-19. The size of a node in the graph corresponds to the magnitude of the net spillover effects. The hues of blue and yellow signifies that the variable functions as a transmitter or receiver of spillover, with the magnitude of the node indicating the intensity of the spillover impact. There is a positive correlation between the thickness of the edge and the magnitude of the net pairwise spillover effect between the two variables. The node indicated by the arrow symbolizes the recipient of spillover.

spillover effects to exchange rate-stock returns, our study adds to the existing knowledge base by providing lesser-known evidence on the African financial market. Furthermore, we identify the root causes of risk accumulation and outbreak as well as the corresponding mechanism of contagion.

It is important to emphasize that average results are primarily beneficial for providing a general overview of the underlying relationships. In reality, average results do not adequately support the examination of interrelations across a range of variables in light of specific significant events (Balcilar et al., 2021). Consequently, a dynamic framework for analysis is crucial. This type of framework not only takes into account the progression of the TCI over time but also illustrates how the function of specific variables within the network may change over time (e.g., from transmitting to receiving or vice versa). Fig. 4 and 5 illustrate the dynamic of total connectedness among the volatilities (high and low) of the equity-currency market and international market volatility. As shown in Fig. 4 and 5, the volatility connectedness among the analysed assets fluctuates over the examined period. Additionally, it is apparent that the volatility connectedness during the pandemic was high indicating a high connectedness between market volatility and African markets. Several studies, including Rai & Garg, (2022), Wen et al., (2021), and Choi, (2022) have also reported similar effects of the COVID-19 pandemic on the volatility connectedness among financial assets. This rise is attributed to the pandemic-induced crisis.

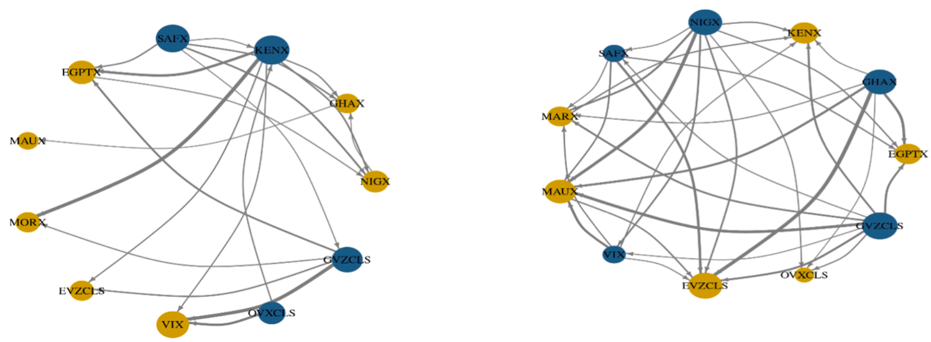
### 4.4. Theoretical and practical implication

Our empirical results primarily indicate that although there is a negative association between the variables studied, the causality direction and the magnitude of the co-movement differ in high and low volatility connectedness. In this regard, our findings offer new perspectives to the existing literature and valuable information for policymakers, portfolio managers, risk managers, and traders to comprehend this connection thoroughly to implement timely and effective policy measures to alleviate market stress during systemic risk. The findings from wavelet coherence reveal that the co-movement between foreign exchange returns and stock returns varies over time at different frequencies during market stress hence policymakers can use this information to hedge and manage the exposure to foreign exchange risk. By having access to more detailed information about the time-varying characteristics of stock and foreign exchange prices, investors can make optimal investment decisions during the systemic risk. In portfolio strategy and asset allocations, it is important to combine the assets of most net recipients and the assets of net transmitters, taking into account investors' risk tolerance and investment. In particular, the increasing impact of most financial assets on others can cause contagion in times of system crisis such as COVID-19 (Asafo-Adjei et al., 2022), as a result, the investor would relentlessly seek net-receiver assets as a measure to mitigate the shocks of other assets (Bossman, Owusu Junior, et al.,



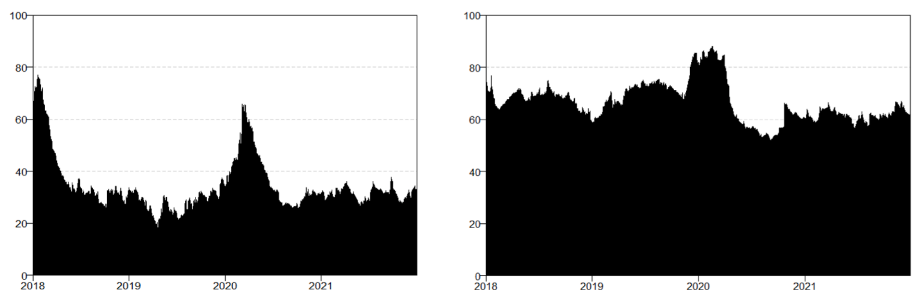

Panel A-Low volatility    Panel B-High volatility

**Fig. 4a.** Network plot for currency market and international market- COVID-19. The size of a node in the graph corresponds to the magnitude of the net spillover effects. The hues of blue and yellow signifies that the variable functions as a transmitter or receiver of spillover, with the magnitude of the node indicating the intensity of the spillover impact. There is a positive correlation between the thickness of the edge and the magnitude of the net pairwise spillover effect between the two variables. The node indicated by the arrow symbolizes the recipient of spillover.



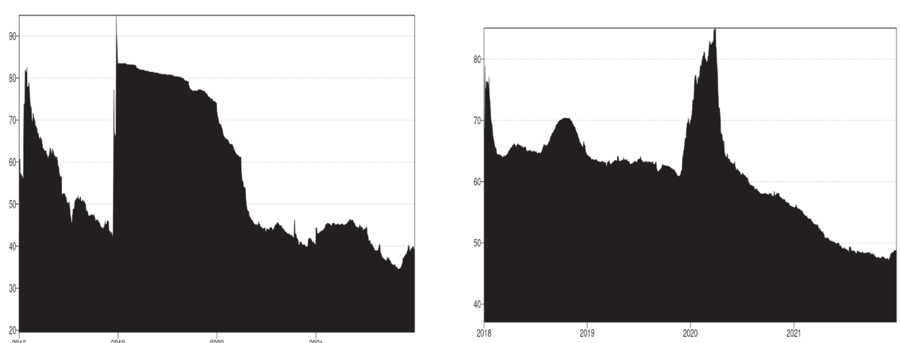

Panel C-Low volatility Panel D-High volatility

**Fig. 4b.** Network plot for currency market and international market- COVID-19. The size of a node in the graph corresponds to the magnitude of the net spillover effects. The hues of blue and yellow signifies that the variable functions as a transmitter or receiver of spillover, with the magnitude of the node indicating the intensity of the spillover impact. There is a positive correlation between the thickness of the edge and the magnitude of the net pairwise spillover effect between the two variables. The node indicated by the arrow symbolizes the recipient of spillover.




Panel A-Low volatility Panel B-high volatility

**Fig. 5a.** Dynamic total connectedness for Equity market and implied volatility.




Panel C -Low volatility Panel D-high volatility

**Fig. 5b.** Dynamic total connectedness for currency and implied volatility.

2022). From the network analysis for stock returns, we notice South Africa is the net recipient in the low volatility before COVID-19 and the net transmitter in the high volatility before COVID-19. However, during the pandemic period, in the high and low volatility, South Africa is a net recipient of shock. This is different from the currency market as we observed a dominant risk spillover before and during health induced crisis. This could be attributed to large trading volumes on the South African market, hence they are prone to significant capital inflows and outflows, which can affect the volatility of the equity market. However, in the case of Kenya, Nigeria and Ghana the shock from the currency market to the equity market is due to the fact that unexpected fluctuations of the currency negatively affect equity market. According to the asset portfolio theory, international investors adjust the proportion of assets they hold to mitigate potential losses from a projected currency value change (Huang et al., 2021). This alteration in asset allocation directly impacts the amount of funds entering or leaving the stock market. Given that these economies are not liquid with rapid information transfer between the two markets exhibit a negative relationship during the health indices crisis with equity return dominating in the negative returns. Given the upward trend before COVID-19 and the negative trend during the pandemic both theories – the flow and oriented model approach can explain the relationship between exchange rates and stocks; however, in South Africa, the stock model approach takes precedence.

Observably we find that the interconnectedness between the African market and market volatilities in high and low volatility for exchange rate −stock returns is impacted by global and regional events during the sample period, which underscores the mutual dependence of these markets on the global financial markets. This behaviour aligns with existing research, which suggests that investors exhibit herd behaviour due to increased uncertainty (Akinsomi et al., 2018). This also supports the idea that proactive portfolio rebalancing and reallocation strategies are necessary during such periods, as investors seek diversification and safe-haven assets, resulting in risk-off strategies adopted by most market participants. This leads to the observed connectedness in the high and low volatility. Furthermore, the highest peaks in connectedness during the health systemic risk, consistent with a large volume of research documenting heightened connectedness among equity-exchange rate returns (Hussain et al., 2024; Boakye et al., 2023; Wang et al., 2023). Our findings provide additional evidence of this phenomenon in the African equity and currency markets, thereby extending and corroborating previous research.

## 5. Conclusion

Understanding the co-movement and spillover of equity and currency markets in the time–frequency domain is crucial for effective asset allocation, portfolio management, and cross-market hedging. This information has become increasingly vital for portfolio managers due to the growing interconnectedness and the significant impact of contagion. To this end, we explore co-movement and volatility spillover between exchange rate-stock returns and implied volatilities for Ghana, Morocco, Egypt, Kenya, South Africa, Nigeria, and Mauritius. We analyse the connectedness dynamics in both static and time-varying employing the DCC-GRACH approach and volatility spillover using BEKK GARCH. We apply a volatility decomposition method of Danielsson et al., (2018) and Xiang & Borjigin, (2024) to acquire high and low volatility from daily returns and we utilise network analysis and DCC-GARCH to examine volatility spillover between exchange rate-stock returns and implied market volatilities.

Our results reveal some practical implications for market participants for policymakers. First, the findings indicate that the co-movement of equity and exchange rates during the pandemic era was exacerbated by world COVID-19 media coverage. The import of the co-movement in time, and frequency domain during COVID-19 suggests that when formulating a policy, the frequency domains which present the trading horizon in a given time frame need to be incorporated. This aims to ensure that the important market dynamics between the COVID-19-related shock, proxied by world media coverage and the financial markets are correctly synchronized in the process of formulating policy actions. Secondly, we observe that the effect of world COVID-19 media coverage has a significant impact across different scales and frequencies except for South Africa(SAF-SAFX) and Egypt (EGPT-EGPTX) which indicate that world COVID-19 media coverage drives a change in the lead-lag interrelationship between equity and exchange returns during pandemic period at low-frequency band. This means that market participants should be cautious about the short-term and medium-term inconsistent market dynamics in Egypt and South Africa, which may make decisions ineffective. Moreover, short-term and medium-term policy measures must be regularly monitored and evaluated since the cone of influence does not cover all short-term and medium-term for Egypt and South Africa. Our finding underscores the significance of world COVID-19 media coverage in determining the co-movement of equity and currency market dynamics in Africa during COVID-19. From the findings of partial wavelet, we observed that when the market participant focuses solely on co-movement between equity and currency markets, some decisions may be compromised given that when world COVID-19 media coverage is incorporated the dynamics of equity and currency markets in Africa change significantly. The complex influence of the co-movement between equity and currency markets stresses the pivotal role of global factors in driving the financial market in Africa (Dragomirescu-Gaina & Philippas, 2022). Therefore, policymakers should not uphold the co-movement of equity and currency markets in the pandemic period as argued by Amewu et al., (2022), on a regional base but consider global factors such as world COVID-19 media coverage. These findings can benefit investors and portfolio managers in formulating cross-country and cross-market hedging and investment strategies. Our results have implications for portfolio managers who can make more informed decisions regarding portfolio allocation of the spillover effects from stock markets to currency markets.

Given the growing difficulties in diversification, specific information on the volatility of financial market connectedness is needed to shrewdly plan hedging strategies. To understand how global market volatility impacts Africa's equity and currency markets, a closer examination of the interdependence between regional and global market volatility was examined to address the negative effect of spillover during COVID-19. Our empiric reveals that VIX and OVXCL play a dominant role in spreading spillovers to both currency and equity markets in Africa. This implies that VIX and OXVCL sentiment can serve as a valuable predictor in Africa's currency and equity market. In the low volatility before COVID-19 for exchange rate-stock return, Kenya Morocco Ghana and Mauritius are the main transmitters of volatility spillovers for Equity markets whereas South Africa and Ghana are the main transmitters for volatility spillovers for the exchange rate. In the high volatility, South Africa is the main transmitter of volatility spillover for both currency and equity markets. However, during health induces crisis, South Africa, Nigeria, Egypt, and Mauritius were the main net recipients of spillover of both high and low volatility for the equity market whereas, in the currency market, South Africa remains the persistent risk transmitter in the low and high volatility whereas Kenya Nigeria and Ghana are net transmitter of risk in the low and high volatility respectively. This finding implies that financial markets exhibit heterogeneity in their capacity to transmit volatility between high and low-investment horizons, underscoring the need for regulators to not only distinguish between risk spreaders and absorbers in financial equity markets but also to appreciate the diversity in the role and location of global markets during the accumulation and outbreak of risk. During the COVID-19 period, contagion is observable with the shock of market volatility (Asafo-Adjei et al., 2022) and it, therefore, becomes prudent for an investor to inexorably search for competing risks and rewards by having knowledge of financial assets such as VIX, OVXCLS, EVZCLS and GVZCLS which have been plugged to have rampage on the financial market hence investors should be mindful of the heterogeneous susceptibility of spillover from market volatility when marking the portfolio decision associated with equity and currency markets during financial imbalance.

In conclusion, the varying roles of different markets as either transmitters or receivers of net flows and implied volatility can be ascribed to market uncertainties during the period of market stress in time scale. This issue warrants further investigation to enhance our understanding of the unique characteristic of exchange rate-stock return by employing conditional CoVAR based on higher order moments to investigate what extent these two markets may be interrelated with each other during extreme market movement. Embarking on this study could yield valuable insights into the dynamics of these markets, which could inform investment strategies and policy decisions. Furthermore, it could substantially enrich the existing body of literature on financial market interdependence and the influence of investor sentiment on market trends.

## CRediT authorship contribution statement

**Godfred Amewu:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Mohammed Armah:** Writing – review & editing, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Saint Kuttu:**

Writing – review & editing, Writing – original draft, Validation, Data curation, Conceptualization. **Baah Aye Kusi:** Validation, Formal analysis, Data curation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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