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Research article

Comovement of african stock markets: Any influence from the COVID-19 pandemic?

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ABSTRACT

Utilising daily data from twelve Sub-Saharan stock markets we investigate the co-movements and information transmission among African stock markets as a result of the impact of COVID while employing multiple wavelet techniques and applying the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to Renyi's and Shannon's effective transfer entropy analysis. The results infer that some number of co-movements exist among stock markets in Africa and that during periods of uncertainties, diversification through the creation of portfolios in African markets is not conducive since they tend to comove strongly during such periods. The study discovered that, a few of the markets responded to the pandemic in leads lags in the pre-, during and post-COVID era, as well as reacted to information transmission. Our findings generally show that information transmission/spillovers are more predominant in the short term than in the medium- and long-term horizons. The Renyi's effective transfer entropy recorded more negative information flows between African stock market than positive information flows, both during the COVID period and after. On the other hand, Shannon's entropy showed non-negative information flow across various time horizons. We conclude that even though most African stock markets were not prone to the contagion effect of the pandemic, it is of vital importance to re-evaluate the notion that African stock markets are immune to contagion of stock market co-movements, especially in times of global uncertainties.

1. Introduction

The COVID-19 pandemic created panic and caused temporary and permanent business closures in several countries. The steady spread of the virus triggered catastrophic repercussions which led to stock market turbulence and partial or total shutdown of economic activities [1]. Several countries employed measures such as, closure of borders to limit international human traffic, and social distancing among others, in an effort to reduce the spread of the virus and eventually eradicate the pandemic. These responses undoubtedly had negative impact on corporate profitability [2,3], stock market volatility [4] and performance of stock markets [5]. As a result of globalisation and openness of economies, stock markets have become susceptible to global economic shocks and uncertainties

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which leads to poor performance [6]. In addition, globalisation has enhanced international capital movement among markets, causing various markets to impact each other's performance [7]. These developments result in co-movements among stock markets [8]. For instance, there was a significant surge in the co-movement of stock markets during the financial crises of the October Crash of 1987 [9]; the 2008 global financial crisis [10,11] and COVID-19 pandemic [12].

The degree of co-movement and interdependence has recently been the subject of empirical studies in African stock markets. This is because, the different levels of interdependence have implications of risk reduction and gains through international portfolio diversification techniques [13]. Despite evidence of interconnections between African and global stock markets during global crisis, some studies have found that their level of integration is relatively weak [14,15]. This offers diversification potential for both local and international investors. It is more important for international investors because emerging market and African stocks are noted for higher returns albeit relatively higher risks. For instance, in 2021, the top 6 performing African stock markets recorded returns between 93 % (Lusaka Securities Exchange) and 16 % (Casablanca Stock Exchange) in hindsight of the recovery from the COVID-19[1] pandemic. The rest are Ghana Stock Exchange (39 %), Malawi Stock Exchange (32 %), Johannesburg Stock Exchange (24 %), and Stock Exchange of Mauritius (17 %).[2] On the contrary, the US stock market which has generated the greatest return, according to Morningstar, boast of an average return of 10 % in the S&P 500 index since it began in1926.[3]

The co-movements among stock markets [8] and stock markets' vulnerability to global economic shocks and uncertainties [6] create a strong possibility that, COVID could have an influence on the co-movement of African stock markets. It is also clear from the literature that co-movements increased during the COVID and other crises periods ([16,17]. Such high levels of co-movement have been described as contagion in the extant literature. Notable amongst them is [7] which clearly differentiates interdependence from contagion. Thus, while this study is premised on COVID, (a stressed market period where financial assets tend to change their course of correlations, usually to high levels, as compared to their fundamental relationships) we look out for contagious episodes in the results. It is noteworthy that studies on the influence of pandemics on co-movement of stock markets of SSA is scanty and most of these studies do not consider a group analysis of SSA but focuses on individual stock markets (see for example [18,19]). The different levels of interdependencies have implications of risk reduction and gains through international portfolio diversification techniques [13]. It is, therefore, evident that, there is some degree of co-movement among stock markets in SSA. This makes this phenomenon a topic of interest in recent times. This study therefore seeks to examine the co-movement between African markets before, during and after the pandemic. Breaking of the study into these phases will determine the influence of COVID on stock market co-movement in Africa.

This study varies from empirical investigations regarding the co-movement of stock markets in SSA as a result of COVID. First, we use the multiple wavelet techniques to examine the co-movement between twelve stock markets in SSA in time and frequency domain. However, methods such as Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models, correlation, panel models, error correction models, vector autoregressive models, and co-spectral analysis often fall short in capturing the time and frequency aspects of the data [20]. This technique also enabled us to examine the effect of COVID cases on the underlying relationships between the stock markets in SSA. The use of the multivariate wavelet allows for the capture of twelve African stock markets as a unit over a range of timescales, in contrast to most previous studies that evaluated co-movement or integration via bivariate platforms. The wavelets analysis handles non-stationarity, non-linearity, structural breaks and localisation in time, and it decomposes time series data into several wavelet time scales [21]. In finance and investment, the wavelet analysis is very useful due to the diverse trading approaches employed by distinct market participants across different investment horizons [22].

Second, this study further uses a novel denoised frequency domain entropy framework to analyse the information flow to the stock markets from COVID. The investigation of the dynamic flow of information between SSA stocks is motivated by the fact that financial markets undergo severe turbulent economic periods posed by information transmission [23]. Investors frequently strive to collect and process information to aid their investment decisions in the financial market, which is a natural venue for information competition [24]. This implies that the timeliness and quality of information is vital for investors [25,26]. The entropy methods (Shannon entropy and Rényi transfer entropy) are therefore adopted to examine the amount of information in a signal series [26] transmitted from the pandemic to stock markets as well as information transmitted among the stock markets over the sampled periods. The data is decomposed using the CEEMDAN into intrinsic mode functions (IMFs), which stand for short-, intermediate-, and long-term time frames. By employing the CEEMDAN-based entropy, we are able to gain a comprehensive understanding of the information flow while considering reduced-noise and different types of investors based on their time-horizons. This approach addresses the issue of mode mixing associated with the Empirical Mode Decomposition (EMD) method and overcomes the limitation of the EEMD in fully eliminating Gaussian white noise following signal reconstruction [27]. The CEEMDAN-based entropy approach stands out for its ability to address asymmetric, nonlinear relationships, and nonstationary challenges. Additionally, it effectively eliminates noise originating from market anxiety, which tends to induce irrational behaviour among market players [28].

Third, we assess the degree of integration between the stock markets in different period samples. This will establish whether the COVID era experienced an increase in co-movement as established in studies on advanced stock markets. This provides a broad scope for the integration analysis between the stock markets and any possible influence from COVID. Fourth, the study also employs [29] non-linear causality to establish causality between COVID and the SSA stock markets as a form of robustness test. This non-parametric test helps to avoid over rejection often observed in the test introduced by Ref. [30]. Overall, the combinations of these techniques provide an all-encompassing dynamic analysis of the dynamic relationships among various frequencies, and potential causal

[1] Hereafter referred to as COVID.

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

[3] S&P 500 (^GSPC) Historical Data - Yahoo Finance.

structures. The application of techniques is supported by the Heterogenous Market Hypothesis (HMH) [31], Adaptive Market Hypothesis (AMH) [32] and Competitive Market Hypothesis (CMH) [33]. The AMH argues that market efficiency varies, and are influenced by factors such as adaptation, innovation, competition, and mutation. The CMH implies that opportunities for profit are dynamic, requiring optimal timing for implementation and active portfolio management. According to the HMH, investors, as part of their trading strategy, analyse events and news, considering implications across various time horizons.

The empirical analyses reveal positive causal relation between COVID and the stock markets. In the short-term, Botswana lags all the other markets but Mauritius lags in the medium-term. South Africa leads all the markets in the medium-term. As the more active markets in Africa, Botswana, Mauritius, and South Africa were the most susceptible to the shocks from the pandemic. The remainder of the paper is organised as follows: the second section reviews the relevant literature on stock market co-movement, followed by the study's methodology. Section four treats the findings and discussion of findings, followed by the conclusions and implications.

2. Review of related literature

2.1. Underpinning theories

Several research efforts have identified the theoretical underpinnings of the stock market co-movement hypothesis. The Information Spillover Effect, the Efficient Market Hypothesis (EMS), and the Behavioural Finance Hypothesis stand out among these. According to the EMS, market pricing for assets is justified by the information available at that time [34]. The links between the securities markets are heavily impacted by subjective factors, such as investor preferences for asset allocation, the size of their stock investment, and the herding effect, in accordance with the behavioural finance theory [35]. The behaviour of investors changes with time, particularly during turbulent periods like the COVID era (2020–2021). Since the market does not function in a vacuum, investors' asymmetrical and market pricing takes time-based behaviour into account. The phenomenon of our discourse is reinforced by Adaptive Market Hypothesis (AMH) [32], Competitive Market Hypothesis (CMH) [33] and the Heterogeneous Market Hypothesis (HMH) [31]. While Cornell [36] contends that investors' rationality (and irrationality) varies across time and among investors, the EMH presupposes that investors' rationality is independent of both time and circumstances. This is because the AMH encourages the study of investor behaviour over tiny sub-samples compared to the whole sample. Cornell [36] captures both the AMH and the HMH. The AMH exhibits different levels of efficiency in contrast to EMH. The HMH further contends that different economic actors use current and past news to determine their investment choices based on varied time horizons, risk preferences, and returns. In addition, during challenging market times, information flow between market precedents when investors' searches become more obstructed. Hence, the AMH, HMH, and CMH further supports the usage of the techniques employed in the study. These techniques provide an all-encompassing dynamic analysis of the dynamic relationships among various frequencies, and potential causal structures.

Theoretically, and to a larger extent, empirically, these investor-generated complexities are believed to span a wide range of markets with varying degrees of risks and returns. This is in line with the portfolio diversification principle. These markets are notable not just for being distinctively different, but also for the competitive risks and returns they offer. Additionally, the asset class that traditional investors diversify into may or may not be the same as the market. Those that satisfactorily satisfy the investor's needs on a competitive basis are referred to as safe havens, particularly under volatile market conditions [13].

Numerous studies have addressed the core concept of portfolio diversification in an effort to achieve competitive returns and risk levels as a result of recent occurrences of financial crises and pandemics/epidemics [37–40]. The fundamental tenet of these and numerous other researches is the notion that investors constantly weigh competing risks and returns, and that this process is intensified in volatile market situations.

2.2. Co-movement of stock markets

The bulk of extant research on co-movement of stock markets focuses on the linkages between developed economies, mostly between US and other developed stock markets [41–43]. Many scholars have been motivated to empirically explore co-movement between Western and African markets and the level and depth of co-integration and movements of stock markets within Africa due to the call for closer links between the African stock markets and other markets. In Africa, the relationships between domestic, regional, and international financial markets in addition to a number of economic factors, have been explored in previous empirical studied [see Refs. [44,45]]. Given the periodic heightened uncertainty in the global markets, emerging markets such as those in Africa present excellent chances for diversification. To determine the feasibility of this assertion, an increasing body of research exploring the co-movements and cross-market correlations between these markets and those of other regions has evolved [46].

The intra-regional return transmission between the seven stock markets of Africa, namely Egypt, Mauritius, Morocco, Namibia, South Africa, Tunisia, and Zambia, was also examined by Ref. [47]. In addition, the authors looked at how relationships changed during the US subprime and European sovereign debt crises, as well as the spill-over effects from six stock markets: UK, China, France, USA, Germany and Japan. Their findings suggest that global market spill-overs had a greater influence on African stock markets than did commodity and currency markets, which had a modest impact. A number of scholars have noted that regional spill-overs inside Africa are less severe than those globally, and as a result, African markets appear to be protected from global crises. Anyikwa and Le Roux [48] examined the level of market integration and contagion between four developed countries (France, Germany, UK, and USA) and seven African stock markets during two key financial crises, namely the global financial crisis of 2008 and sovereign debt crisis of the Eurozone. They adopted the ARDL and DCC-GARCH models and discovered limited evidence of market integration among advanced and African nations. In addition, Atenga and Mougoué [46] investigated financial market return and volatility spill-overs from Brazil, China, France, Germany, Japan, Mexico, Russia, the UK and the US to seven stock markets in Africa. The findings of the study indicated a rather feeble transfer of external shocks to stock markets in Africa, notwithstanding the fact that significant spill-overs occurred during the global crises of 2008 and 2012. The reviewed literature so far indicates scanty research on co-movement between African stock markets even though there have been calls for the integration of the African stock market over the past two decades ([49,50]. The few that have been produced indicate a weak or no co-movement between African stock markets.

2.3. Co-movement of stock markets during uncertainties

In studying the relationship between stock markets, it is important to distinguish between interdependence and contagion as indicated in Ref. [7]. They provide evidence of heightened correlations the fundamental levels of connectedness during periods crisis which they term as contagion. Asymmetric information and physical exposure are widely regarded as the two main mechanisms for contagion transmissions. As a result, a shock in one market may cause shocks in others, regardless of the established fundamentals [7, 51]. Forbes and Rigobon [7] discovered that although there were periods of stronger correlation between markets, particularly during periods of uncertainties, this was mainly because of common shocks that impact multiple markets instead of shocks spreading directly from one market to another. Co-movement is more frequently caused by common factors or growing market interdependence than by direct transmission of shocks. They highlight that, rather than shocks transmitting directly from one market to another during a crisis, common factors or shared shocks can cause correlated movements across markets. This suggests that developments or events in one market directly impact other markets creating disproportionate effects, usually unrelated or slightly connected. The findings of heightened correlation among markets especially during periods of uncertainties have been reinforced by latter studies. For instance, stock markets experienced a significant surge in comovement during the October Crash of 1987 [9], the global financial crisis of 2008 [11], and the COVID-19 pandemic [12]. In this study, we delineate interdependence from contagion as we distinguish the impact from the pandemic in the co-movement among the African stock markets.

The subject of financial crises and its related co-movement between stock markets has been extensively published in literature since the 1970s. Most of these studies conclude that there is significantly less interconnectedness between countries than there is within a country in terms of stock price movement [52,53]. Several of these studies established a presence of low correlation between the world's major stock markets prior to the 1987 crisis. However, this correlation increased during the crash and then abruptly decreased following the crash. The premise that financial crises may deepen interconnectedness by affecting financial markets locally, regionally, or even globally was reinforced by evidence from empirical studies [16,54]. Lee and Jeong [17] in their study on the extent of integration between European markets and other international markets, established that co-movement between the stock markets grew stronger during the 2008 crisis and reduced significantly thereafter. Their findings have been reiterated by Ref. [16]. Measuring cross-correlations between the US stock market and eight other stock markets (the remaining members of the G7 plus China and Russia), Tilfani et al. [55] discovered that while correlation levels with the US stock market decreased prior to the crisis, the results show a contagion effect after the crisis.

According to Lee and Kim [56], co-movement across markets, a short-term link that represents the market speed ratio between two markets is crucial to the mechanics of contagion. They claim that contagion is quite likely to happen when a break in the short-term link (market speed ratio) results in the disruption of a long-term relationship (change in co-movement). In their study on financial contagion across G10 stock markets during market crises, BenSaida and Litimi [57] indicate a high indication of contagion during the global financial crisis of 2008–2009 and the European sovereign debt crisis. However, it is important to note that, there was no significant contagion during the market crisis of 2002 as a result of the absence of market integration at the time. Escribano and Iniguez [58] studied the impact of Brexit process on the world's financial markets from the start of 2016 and the conclusion of 2018. Their findings point to financial contagion on the major European and global economies as a result of the Brexit referendum results and the ensuing rise in uncertainty.

2.3.1. Epidemics/pandemics

The effect of epidemics and pandemics on stock market co-movements has received very little attention, despite the fact that recent worldwide developments in the global capital market have substantially enhanced the knowledge of scholars on the issue. It is notable that the preponderance of studies suggests that contagious diseases like Ebola, SARS, swine flu, and Zika had little to no impact on financial markets. For instance, Nippani and Washer [59] did not discover any evidence of spread to the stock exchanges of Canada, Hong Kong, Indonesia, the Philippines, Singapore, and Thailand in their investigation of the SARS outbreak in these financial markets. Several studies have reiterated these findings (see Refs. [60,61]. A considerable number of studies have examined how COVID promotes the interconnectedness of the global financial market. Employing the spill-over technique developed by Refs. [62,63], focusing on G20 nations, evaluated how returns and volatility connectedness were affected by COVID phases and fatalities.

It is imperative to note that, despite the fact that studies examining the influence of COVID on the returns and volatility of stock markets in Africa are fairly common [see Refs. [5,64]]), it is regrettable that the impact of the pandemic on the interconnectedness and dependency of African stock markets has received little attention. It is imperative to state that only a few researchers have studied the co-movement of African stock markets [[65–67]. Omane-Adjepong, Alagidede et al. [65] for instance, found that co-movements of pairwise series became stronger (0.70–0.89) and attained its peak during the COVID pandemic than the period before the COVID era (−0.49–0.36). These findings support the assertion that crises have a significant impact on co-movement of stock markets. Once more [65], argue that the COVID pandemic had little influence on the pairwise correlation of the equity markets of Africa. African markets thus epitomise reliable markets for diversification and risk management.

Owusu Junior et al. [28] studied the chaotic transmission of information from COVID pandemic to 27 global stock markets from

December 31, 2019, to April 18, 2021. Their findings support the notion that short to medium-term diversification potentials are higher. Their findings reiterate that of [20] who discovered that, compared to higher frequencies (short-term and medium-term), African stock markets have fewer diversification possibilities at lower frequencies. This suggests that co-movement is often strong over the long term but weak over the short term.

Bantes [68] discovered that COVID-19 has a major impact on precious metal volatility in his study on stylized facts related to the volatility of precious metals before and during the pandemic. The four metals show a moderate persistence in the pre-COVID-19 sub-period, but this influence disappears with the crisis eruption. Additionally, positive asymmetric effects are shown in the volatilities of gold and silver, which increase throughout the COVID-19 phase. He credits these metals' hedge/safe-haven qualities for this phenomenon. In contrast, they discovered a different trend in the volatilities of palladium and platinum, which show negative asymmetry prior to the pandemic, in connection with financial markets. These metals exhibit conflicting results following the crisis. Additionally, Bentes et al. [69] look into how COVID-19 affects the seasonality of gold returns. They discover that during the COVID-19 epidemic, the so-called "autumn effect," or the customary seasonal increase in gold returns in the fall, disappears and even exhibits a reverse trend. They attribute this phenomenon to the declining demand for gold, which fell significantly in the third quarter of 2020. In contrast, and consistent with previous studies on this subject, they find no indication of seasonal influences in gold volatility. Their findings support gold volatility's beneficial asymmetric effect. Again, Nkrumah-Boadu et al. [70] examined the inter-dependencies between cryptocurrencies, gold and a few African stock markets in a temporal frequency domain in the period prior to and during the COVID pandemic. The results indicate that cryptocurrencies and gold offer investors in African stocks a safe haven, opportunities for diversification, and hedge, particularly in the short run in the COVID era.

Some research indicated that the COVID-19 pandemic fuelled stock market contagion. Fu et al.'s [71] study on the effect of the COVID-19 epidemic on the stock markets of fifteen nations in Asia, Europe, Latin America, and North America suggested that contagion effects extend to global equity markets in the four areas studied. Furthermore, the study identified Asia to be the region with the least susceptibility to the risks of contagion, followed by Europe and North America. It is determined that Latin America has the highest probability of being impacted by the crisis severity index based on its temporal window. The findings support the notion that stronger contagion effects occur in nations with more severe epidemics.

Given that the pandemic transmits various chaotic information over varying time frames, the findings enable policymakers and investors to take informed decisions. From the review of literature so far, we assert that much attention has not been given to co-movement between stock markets in Africa especially during periods of uncertainties. This study seeks to ascertain the propensity of this inactive co-movement to be triggered by periods of uncertainties such as the upsurge of the COVID pandemic.

3. Methodology

3.1. Wavelet multiple correlation (WMC) and cross correlation (WMCC)

The WMC is denoted by $\Omega X(\lambda_j)$ and described by Ref. [72] as a number of multiscale coherences computed through Xt as shown. The roots squared of R^2 of the regression created by combining $w_{ijt}, i = 1, 2, ..., n$ variables in a linear way for which R^2 is highest is achieved at each scale λ_j. Empirical works show that no auxiliary regressions should run as the R^2 conforms to the regression variable z_i $\{z_k, k \neq i\}$ shown as $R_i^2 = 1 - \rho^{-ii}$, and ρ^{ii} = the ith diagonal component of the correlation matrix P that is complete and inverse. Therefore, WMC is presented in equation (1) as

$$\Omega X(\lambda j) = \left(1 - \frac{1}{max\ diag P_j^{-1}}\right)^{1/2} \tag{1}$$

where Pj is the correlation matrix of W_{jt} in the form $(n\ x\ n)$.

By permitting a lag τ at each scale λ_j between observed and adapted numbers, the WMCC in equation (2) can be derived as

$$\Omega X, \tau(\lambda_j) = Corr\left(w_{ijt}, \widehat{w}_{ijt+\tau}\right) = \frac{Cov\left(w_{ijt}, \widehat{w}_{ijt+\tau}\right)}{Var\left(w_{ijt}\right) Var\left(\widehat{w}_{ijt+\tau}\right)} \tag{2}$$

where for $n = 2$, WMC and WMCC align with conventional wavelet correlation and cross-correlation. For an extensive presentation of method, see Refs. [18,28,73,74].

3.2. CEEMDAN

The CEEMDAN was introduced by Ref. [75] to address the deficiencies in EEMD. This was done by adding the noise to the prior iteration's residual, deviating from the conventional approach of incorporating it into the original signal, as mentioned by Ref. [76]. The CEEMDAN-based entropy technique addresses the Heterogeneous Market Hypothesis (HMH) [31], the Adaptive Market Hypothesis (AMH) [32], and the Competitive Market Hypothesis (CMH) [33]. It is noteworthy that the CEEMDAN output conforms to the Gaussian distribution, resulting in the IMFs adhering to N (θi, 1) as detailed in Ref. [77].

The stock returns were decomposed into a residual and six IMFs with the R package called libeemd [78]. We start with N, noise parameters, index for IMF and perform the EMD for N. The ensemble mean IMFs are calculated in equation (3) as

$$\overline{IMF_n(t)} = \frac{1}{N}\sum_{n=1}^{N} IMF_n(t) \tag{3}$$

This goes through a number of steps. The last step is to compute the j^{th} residue, where $j = j + 1$ in equation (4) as

$$r_j(t) = r_{j-1}(t) - \overline{IMF_j(t)} \tag{4}$$

For a comprehensive overview of the methodology, please refer to the following works: [33,79,80].

3.3. Effective transfer entropy

The Shannon entropy is a fundamental concept in information theory that underpins the idea of transfer entropy, which quantifies uncertainty in a system ([81].

It is presented in equation (5) as

$$T_{J\longrightarrow I}(k,l) = \sum P\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) log \frac{P\left(i_{t+1}\middle| i_t^{(k)}, j_t^{(l)}\right)}{P\left(i_{t+1}\middle| i_t^{(k)}\right)} \tag{5}$$

where $T_{J\longrightarrow I}$ calculates the information flow from J to I.

Building upon Shannon's entropy, we introduce Rényi Transfer Entropy (RTE), which depends on a weighting parameter “q" [82], and calculated in equation (6) as

$$H_J^q = \frac{1}{1-q} log \sum_j P^q(j) \tag{6}$$

with $q > 0$.

Relying on the escort distribution ([83], $\varnothing_q(j) = \frac{p^q(j)}{\sum_j p^q(j)}$ with $q > 0$, normalises the distribution and RTE (in equation (7)) is derived as

$$RT_{J\longrightarrow I}(k,l) = \frac{1}{1-q} P\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right) log \frac{\sum_i \varnothing_q\left(i_t^{(k)}\right) P^q\left(i_{t+1}\middle| i_t^{(k)}\right)}{\sum_{i,j} \varnothing_q\left(i_t^{(k)}, j_t^{(l)}\right) P^q\left(i_{t+1}\middle| i_t^{(k)}, j_t^{(l)}\right)} \tag{7}$$

[see Refs. [33,74,79]].

3.4. Non-linear causality for robustness check

Given the non-linearity established in the stylized facts of our variables, captured in the wavelets techniques in addition to causality this impliedly addressed in the entropy, we conduct a robustness check with a non-linear causality test. The Diks and Panchenko [29, 84] non-linear causality test is adopted to assist in determining whether the pandemic is a cause or effect of SSA stock markets.

We let X_t and Y_t denote two variables that are stationary and dependent time series while $F_{X,t}$ and $F_{Y,t}$ is the information sets of past observations of X_t and Y_t, before time t −1 respectively. '∼' shows the equivalence in distribution, then in equation (8) the time series X_t Granger causes series Y_t, for some $k \geq 1$

$$(Y_{t+1}, \ldots, Y_{t+k})\left|\left(F_{X,t}, F_{Y,t}\right) \sim (Y_{t+1}, \ldots, Y_{t+k})\right| F_{X,t} \tag{8}$$

A natural estimator of q is deduced and expressed in equation (9) as

$$T_n(\varepsilon_n) = \frac{(2\varepsilon_n)^{-d_X - 2d_Y - d_Z}}{n(n-1)(n-2)} * \sum_i \left[\sum_{k,k\neq i}\sum_{j,j\neq i}\left(I_{ik}^{XYZ}\, I_{iJ}^{Y} - I_{ik}^{XY}\, I_{iJ}^{YZ}\right)\right] \tag{9}$$

The t-statistics $T_n(\varepsilon_n)$ of the Diks and Panchenko [29] is simplified in equation (10) to

$$T_n(\varepsilon_n) = \frac{(n-1)}{n(n-2)} * \sum_i \left(\widehat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\, \widehat{f}_Y(Y_i) - \widehat{f}_{X,Y}(X_i, Y_i)\widehat{f}_{Y,Z}(Y_i, Z_i)\right) \tag{10}$$

[see Refs. [29,84].

3.5. Data and summary statistics

The study utilises data from Sub-Saharan stock markets - Botswana, Egypt, Ghana, Kenya, Mauritius, Morocco, Nigeria, South Africa, Tanzania, Tunisia, Zambia and Zimbabwe. The data spans January 2012 to March 2023. The data set is divided into pre, during and post COVID-19 period. The pre-COVID is from January 2012 to February 2020. For during COVID and post COVID periods, we have from March 2020 to February 2021 and from March 2021 to March 2023, respectively. These sub-samples are based on the fundamental analysis of information pertaining to the pandemic, especially provided by the WHO and the extant literature (see also [12]). Data on the stock markets were obtained from EquityRT (https://equityrt.com/) whereas COVID-19 data was obtained from Our World in Data (https://ourworldindata.org/). In Table 2, we also present the [85] (ZA-SB) structural break test to corroborate the

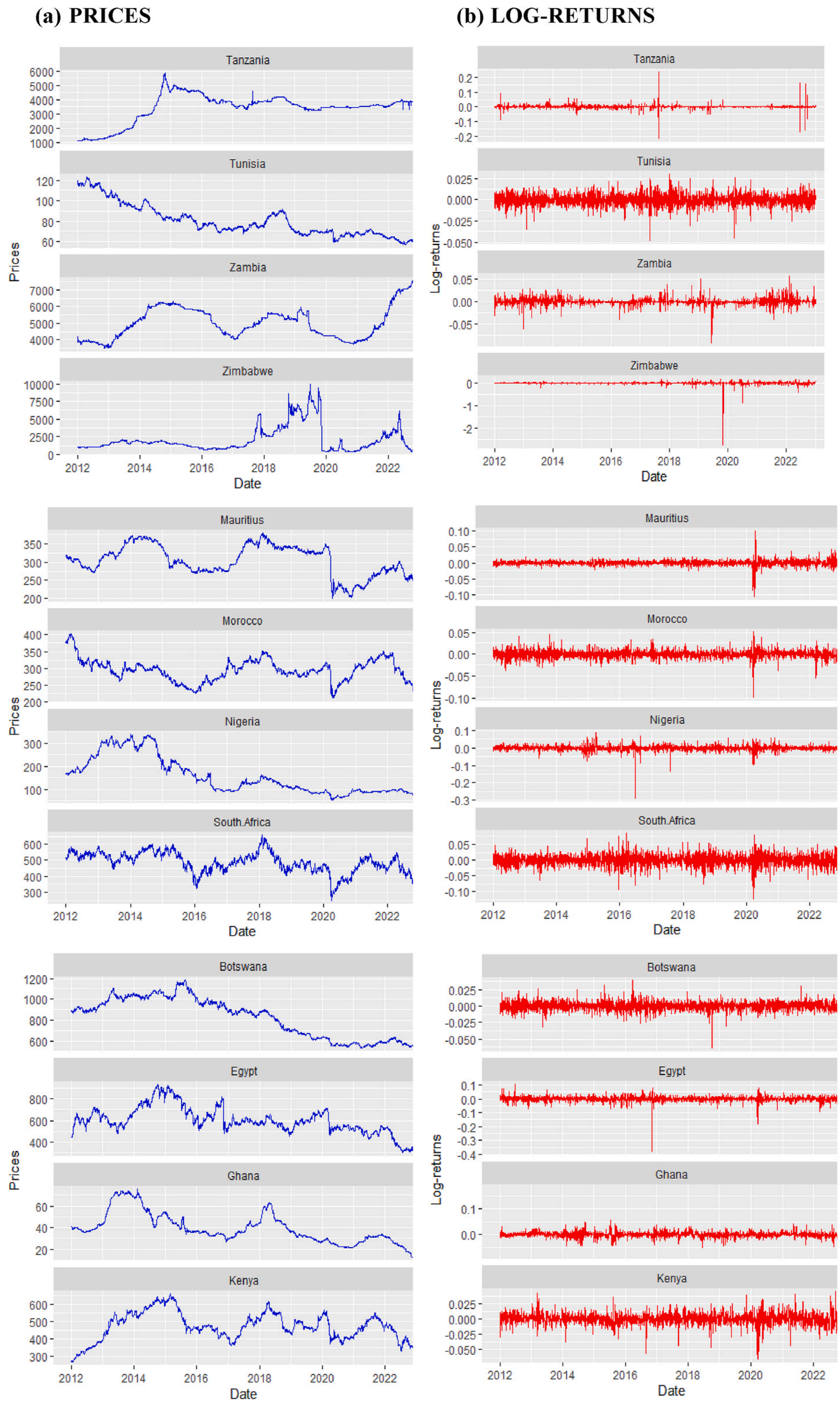

Fig. 1. Price and returns series plots. *Note: Prices in panel (a) and Log-returns in panel (b).*

sub-samples. While, the markets show different break points notable ones that align with the COVID periods include for Mauritius, South Africa, Zambia, and Zimbabwe. It is common for statistical tools to present results that do not conform totally with the market dynamics that is the reason we sub-sample based on the real market information and literature pertaining to the pandemic.

We used the daily returns, $r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$, where r_t is the return that is compounded continuously, while P_t *and* P_{t-1} are the current and previous indexes respectively. Fig. 1 indicates fluctuating prices (Fig. 1 (a)) and returns (Fig. 1 (b)) of the stock markets over time. Notably, there is a resemblance in the variations, particularly during 2020. The downward trends in the data can be ascribed to the impact of the COVID-19 pandemic. Additionally, the price series for these stocks exhibit an upward trajectory after the pandemic.

Table 1 presents the summary statistics for the observations full, before, during and after COVID sample periods. According to the Table, the average values, while not exhibiting significant differences, show a slight decrease in magnitude during the pandemic when compared to the pre and post COVID periods. Similarly, as compared with the pre- and post-periods of the pandemic, the standard deviation indicates that all stock prices displayed higher levels of volatility during the pandemic era. The presence of negative skewness values suggests that the majority of variables are skewed to the left, highlighting an absence of symmetric distribution and the existence of longer tails on the left side of the distribution. The statistics further reveals that the stocks irrespective of the period are leptokurtic with a recorded kurtosis value more than 3. Meanwhile, for pre COVID Mauritius and Morocco while for during COVID period Botswana and Ghana and post COVID period, Kenya, Nigeria, South Africa and Tunisia exhibited light-tailed distributions with

Table 1
Summary statistics.

	COVID	Mean	Std. Dev.	Skewness	Kurtosis	Normtest.W
Botswana	Full	−0.0001	0.0061	−0.4508	6.2982	0.9587***
	Pre	−0.0002	0.0063	−0.5686	7.3823	0.9494***
	During	−0.0004	0.0059	−0.4556	0.1249	0.9841**
	Post	0.0001	0.0055	0.2715	2.2857	0.9788***
Egypt	Full	−0.0001	0.0176	−4.2899	83.2691	0.7684***
	Pre	0.0002	0.0173	−5.4112	116.3484	0.7510***
	During	−0.0009	0.0206	−3.2090	27.5427	0.6721***
	Post	−0.0007	0.0176	−0.8046	7.1680	0.8799***
Ghana	Full	−0.0003	0.0110	1.3566	35.1570	0.8192***
	Pre	−0.0002	0.0097	−0.1570	4.6141	0.9171***
	During	−0.0003	0.0068	−0.0323	1.0783	0.9703***
	Post	−0.0010	0.0162	2.5057	37.3375	0.6936***
Kenya	Full	0.0000	0.0088	−0.5674	5.7261	0.9354***
	Pre	0.0003	0.0078	−0.2653	4.7018	0.9497***
	During	−0.0002	0.0126	−1.4575	5.8305	0.8868***
	Post	−0.0008	0.0099	−0.0421	2.8727	0.9631***
Mauritius	Full	−0.0001	0.0076	−1.1053	41.0453	0.7961***
	Pre	0.0000	0.0051	−0.0441	1.3920	0.9848***
	During	−0.0014	0.0167	−1.1411	16.4315	0.7182***
	Post	0.0001	0.0086	0.6229	3.4525	0.9458***
Morocco	Full	−0.0002	0.0090	−0.7836	9.8161	0.9281***
	Pre	−0.0001	0.0082	0.1301	2.2719	0.9752***
	During	−0.0001	0.0140	−2.0906	14.0715	0.8060***
	Post	−0.0006	0.0092	−0.8293	4.5507	0.9353***
Nigeria	Full	−0.0002	0.0144	−3.3286	61.9762	0.8156***
	Pre	−0.0004	0.0147	−3.9202	75.0801	0.8032***
	During	0.0006	0.0206	−1.2045	5.6088	0.8798***
	Post	−0.0001	0.0084	0.0586	1.6430	0.9787***
South Africa	Full	−0.0001	0.0177	−0.4646	3.7024	0.9659***
	Pre	−0.0001	0.0166	−0.2859	2.3276	0.9769***
	During	0.0009	0.0256	−1.1491	5.1731	0.9081***
	Post	−0.0003	0.0173	−0.0138	0.5919	0.9955***
Tanzania	Full	0.0004	0.0112	0.6373	170.8796	0.3713***
	Pre	0.0005	0.0108	1.2091	180.9470	0.4610***
	During	0.0000	0.0013	−3.9743	28.3686	0.4630***
	Post	0.0003	0.0147	−0.3883	100.1153	0.2065***
Tunisia	Full	−0.0002	0.0066	−0.3679	3.8605	0.9660***
	Pre	−0.0002	0.0066	−0.2779	3.4619	0.9715***
	During	−0.0002	0.0081	−1.0641	5.9034	0.9034***
	Post	−0.0001	0.0060	0.0460	1.0560	0.9898***
Zambia	Full	0.0002	0.0068	−0.8226	28.0250	0.6821***
	Pre	0.0000	0.0065	−2.0567	37.5082	0.6497***
	During	−0.0002	0.0042	−0.3272	4.4371	0.7616***
	Post	0.0013	0.0085	1.2230	8.6406	0.7835***
Zimbabwe	Full	0.0001	0.0623	−30.1642	1293.4087	0.2639***
	Pre	−0.0001	0.0645	−36.2203	1538.3032	0.1438***
	During	0.0011	0.0762	−5.8742	63.9805	0.6097***
	Post	0.0005	0.0437	−1.4514	15.1338	0.8803***

kurtosis values smaller than 3. The Shapiro-Wilk statistics showed that all the variables were non-normally distributed irrespective of the period. It is noticeable that the variables are stationary at both level and first difference from the KPSS results presented in Table 2. The ADF results was stationary for first difference and at level during the pandemic.

Table 2
Structural break and unit root tests.

Market	ZA-SB	ZA-SB break point			
Botswana	−3.6014***	2018-03-26			
Egypt	−4.725***	2013-09-06			
Ghana	−2.3436***	2012-07-25			
Kenya	−2.7661***	2022-02-21			
Mauritius	−3.2977***	2020-02-14			
Morocco	−3.11***	2022-02-10			
Nigeria	−4.8122***	2014-10-08			
South Africa	−4.365***	2020-10-29			
Tanzania	−3.7796***	2013-09-27			
Tunisia	−3.582***	2012-09-14			
Zambia	−2.5079***	2021-10-28			
Zimbabwe	−5.4168***	2019-10-25			
	COVID	**ADF**		**KPSS**	
		Level	**First difference**	**Level**	**First difference**
Botswana	Full	−2.5558	−13.832***	25.551***	0.26564*
	Pre	−1.9929	−13.044***	15.103***	0.56084**
	During	−4.0695***	−5.6064***	0.53211**	0.24656*
	Post	−1.8499	−7.2345***	1.6309***	0.10229*
Egypt	Full	−3.7336**	−13.629***	13.519***	0.15345*
	Pre	−3.0934	−12.736***	3.7567***	0.092431*
	During	−5.364***	−7.202***	0.090403*	0.22751*
	Post	−1.7719	−7.4022***	4.7247***	0.10556*
Ghana	Full	−2.5891	−10.767***	15.619***	0.27577*
	Pre	−2.1835	−9.6897***	6.7979***	0.28322*
	During	−0.019324	−4.8049***	1.6016*	1.8818***
	Post	−2.4603	−6.4392***	6.6613***	0.24754*
Kenya	Full	−2.4874	−13.852***	2.8737***	0.62651**
	Pre	−2.4018	−11.602***	2.7747***	0.47891**
	During	−4.7415***	−5.8287***	0.7037***	0.32194*
	Post	−2.6004	−7.6836***	6.7332***	0.26614*
Mauritius	Full	−2.0193	−13.319***	7.5322***	0.095533*
	Pre	−1.4233	−11.988***	2.5788***	0.13095*
	During	−5.3665***	−5.542***	0.69272***	0.3561*
	Post	−1.587	−8.8074***	1.5588***	0.58155**
Morocco	Full	−2.8838	−12.187***	2.3396***	0.1003*
	Pre	−2.6285	−12.438***	3.3221***	0.21145*
	During	−7.6672***	−5.0967***	3.4154***	0.38758*
	Post	−2.4591	−8.0486***	6.504***	0.34014*
Nigeria	Full	−2.2494	−12.64***	21.342***	0.14797*
	Pre	−2.4322	−12.396***	16.486***	0.3378*
	During	−2.2265	−5.8744***	3.8089***	0.20539*
	Post	−1.91	−8.0727***	1.9349***	0.10282*
South Africa	Full	−3.5229	−14.807***	9.2214***	0.019904*
	Pre	−2.9697	−14.35***	4.4058***	0.054915*
	During	−4.6054***	−6.2432***	3.6301***	0.11574*
	Post	−2.5531	−7.857***	4.4552***	0.048956*
Tanzania	Full	−1.8612	−11.278***	8.376***	1.4233***
	Pre	−1.1549	−10.703***	10.344***	1.6631***
	During	−2.3305	−5.8431***	0.61628**	0.18056*
	Post	−1.8005	−10.094***	6.5056***	0.032841*
Tunisia	Full	−2.3849	−12.996***	22.565***	0.1223*
	Pre	−1.866	−11.677***	17.533***	0.15802*
	During	−4.0848***	−6.4463***	1.8519***	0.13897*
	Post	−1.0602	−8.1753***	5.7906***	0.17112*
Zambia	Full	0.11001	−12.568***	3.7186***	0.4801**
	Pre	−1.0309	−11.664***	3.6535***	0.4861**
	During	−0.86484	−6.6875***	2.5646***	0.55658**
	Post	−1.2308	−7.6051***	7.5574***	0.26652*
Zimbabwe	Full	−3.1116	−13.18***	2.8943***	0.0415*
	Pre	−2.8468	−12.372***	9.0475***	0.10003*
	During	−2.1601	−5.3323***	0.55131**	0.16788*
	Post	−2.1079	−7.7382***	1.8488***	0.23185*

[***, **, *] indicates significance at 1 %, 5 %, and 10 % respectively. ZA-SB is Zivot and Andrew (1992) unit root test with unknown structural breaks.

4. Results and discussions

4.1. WMC and WMCC

We move on to calculate the WMC and WMCC, which effectively breaks down the return series into localized time-frequency components using the MODWT method introduced by Ref. [72]. The multivariate wavelet analysis has significant implications for individuals involved in financial markets, as it aids them in efficiently evaluating their investment time-frames across different frequency bands when making decisions related to asset allocation, portfolio diversification, and risk management. Fig. 1 and Table 2 present the results for WMC while Fig. 2 and Table 3 present the results for WMCC.

Fig. 2 visually represents the WMC of SSA stock markets' returns. The numerical findings, presented in Table 3, provide additional support. A rising trend of WMC is observable for the full sample period (Fig. 2(a)). Furthermore, Fig. 2 demonstrates that the WMCs exhibit both upward and downward trajectory as the time-scales increase. The numerical results in Table 3 support these illustrative deductions. The WMC coefficient of 99.15 % is found for the full sample (96.63 % and 99.79 % at the lower and upper confidence bounds, respectively) (Fig. 2(a)). The WMC for COVID period is almost one (1), which is 99.97 %, and is at scale 16 of inter-dependency (Fig. 2(c)).

This is the same for post-COVID period (Fig. 2(d)) but achievable at inter-dependency scale of 32. The pre-COVID (Fig. 2(b)). Saw a rise in WMC from scale 1 to 16 and fell at scale 32. The remaining factors during the period account for more than 99.99 % of the daily returns of any SSA stock market at scale 64 to 128. The WMC continued to be high in post COVID era even though the values reduce slightly at scale levels. WCI increased during the COVID era but the intensity reduced slightly in period after the pandemic.

The strong connections between the African stock markets can be interpreted to be the cause of the high market integration. The increased inter-connectedness observed during the pandemic can be explained and supported by Owusu Junior et al.'s CMH [33]. According to the CMH, during crisis periods, there is a higher flow of information and spill-overs between different assets or asset classes. Partly, this is due to rational but sometimes irrational investors actively searching for safe assets that can optimize their portfolio objectives. The findings also depict those periods of uncertainties such as pandemics/epidemics are not conducive for diversification through creation of portfolios in African markets since they tend to comove strongly during periods of uncertainties. As a result, investors may look to diversify their holdings by seeking stocks from other markets, which can help protect them against potential losses experienced by their existing assets in the portfolio [86].

Furthermore, the results suggest that some amount of co-movement exist among African stock markets contrary to what previous scholars have reported [49,50]. This finding supports that of [87] who also established that co-movement among some selected African countries became stronger and attained the peak during the COVID epidemics and reduced in the post-COVID era.

The confirmation of the lead/lag market across different wavelet scales is supported by the pictorial results depicted in Fig. 3 and the numerical results presented in Table 4. These results specifically pertain to the WMCC for SSA stock markets. From the full sample (Fig. 3(a)), Botswana tends to be the potential lead or lag at lag 0 for scale 1–2. This means that Botswana stock market is the first or last to respond or recover from shocks relative to the other markets in the short term. Botswana seems to be the probable lead or lag series from the entire sample at lag 0 for scale 1–2. This indicates that, in comparison to the other markets, the Botswana stock market is either the earliest or the last to react to or recover from shocks in the short term. South Africa has the ability to either lead the market in the medium term or lead the market in the long-term with Mauritius at scale 64–128. At scale 32, Mauritius responds or recovers from

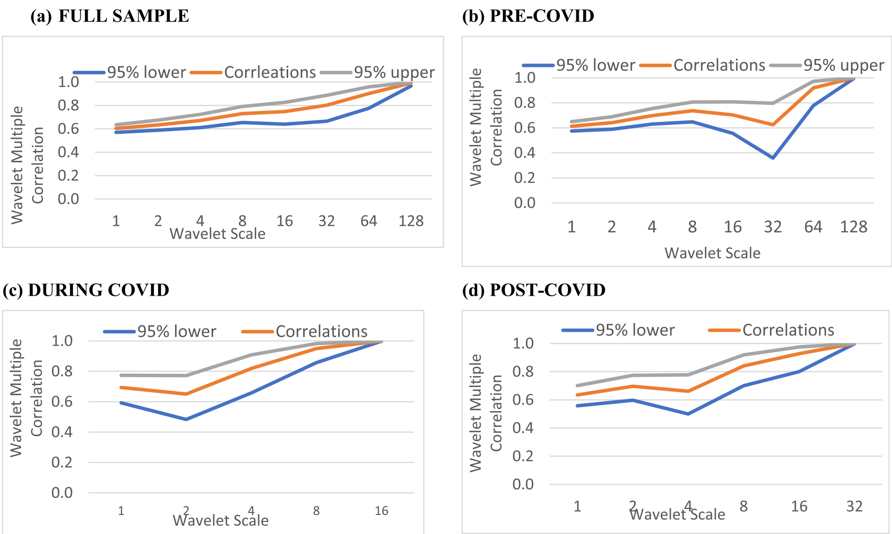

Fig. 2. Wavelet Multiple Correlations (WMC) . *Note: Panels (a), (b), (c), and (d) denote WMC for full sample period, pre-COVID period, COVID period, and post-COVID period, respectively.*

Table 3
Wavelet multiple correlations (WMC).

Scale	WMC 'lower'	Correlation	WMC 'upper'	WMC 'lower'	Correlation	WMC 'upper'
	FULL SAMPLE			PRE-COVID		
1	0.5697	0.6033	0.6349	0.5748	0.6137	0.6498
2	0.5880	0.6335	0.6749	0.5889	0.6418	0.6892
4	0.6108	0.6713	0.7240	0.6305	0.6978	0.7548
8	0.6540	0.7298	0.7911	0.6485	0.7373	0.8064
16	0.6397	0.7472	0.8260	0.5565	0.7038	0.8081
32	0.6648	0.8019	0.8867	0.3587	0.6250	0.7973
64	0.7756	0.9022	0.9590	0.7780	0.9192	0.9720
128	0.9663	0.9915	0.9979	0.9941	0.9990	0.9998
	DURING COVID			POST-COVID		
1	0.5923	0.6937	0.7735	0.5578	0.6348	0.7009
2	0.4831	0.6503	0.7718	0.5975	0.6961	0.7741
4	0.6577	0.8186	0.9081	0.4997	0.6606	0.7774
8	0.8572	0.9495	0.9827	0.7002	0.8413	0.9191
16	0.9982	0.9997	0.9999	0.8003	0.9279	0.9751
32	0	0	0	0.9982	0.9997	0.9999

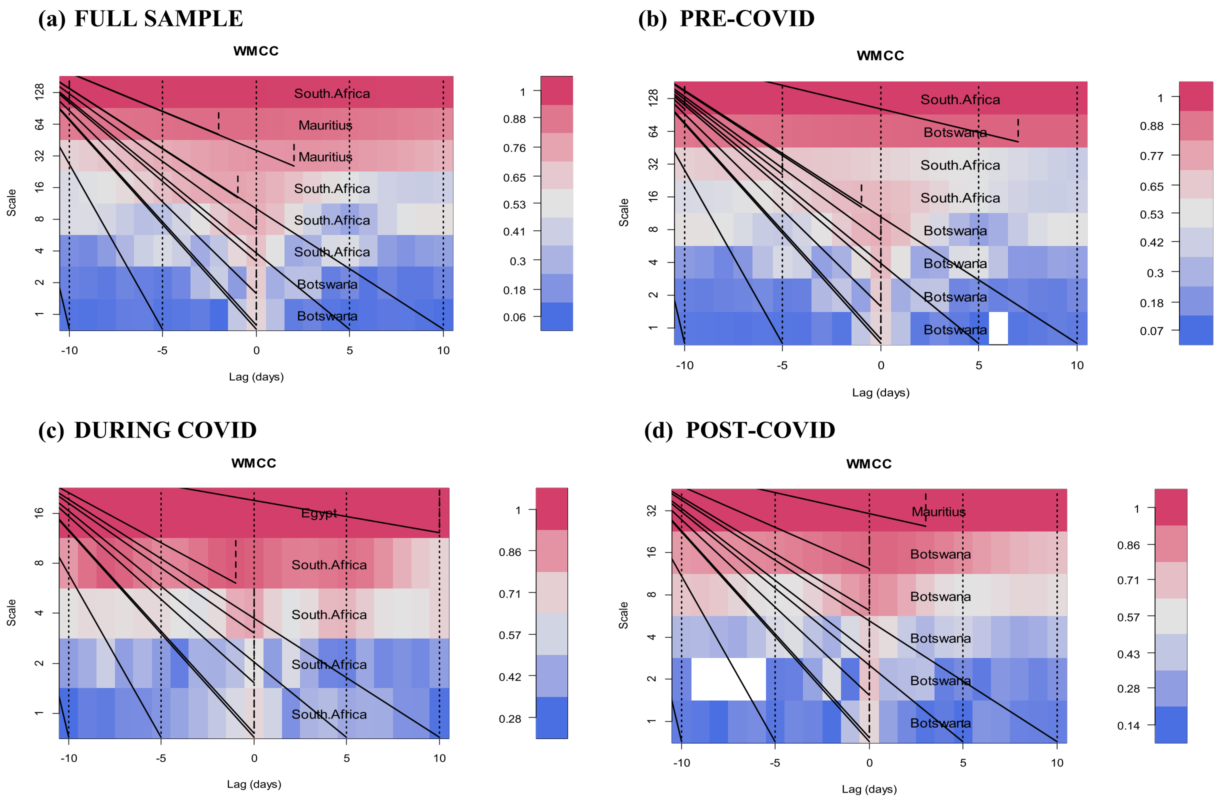

Fig. 3. Wavelet Multiple Cross-Correlations (WMCC). *Note: Panels (a), (b), (c), and (d) denote WMCC for full sample period, pre-COVID period, COVID period, and post-COVID period, respectively.*

any shocks last.

For the pre-COVID period (Fig. 3(b)), Botswana is able to lead or lag the market in the short-to-medium term and lag in the long term while South Africa leads the market in medium-to-long term. Over the COVID period (Fig. 3(c)), South Africa leads or lags the market at scale 1–4 and lead at scale 8. Surprisingly, we have Egypt lagging in the long term. Botswana stock market, again, has the ability to lead or lag the market for the post-COVID (Fig. 3(d)) period at scale 1–16 of inter-dependence as Mauritius lags the market in the long term. The indices of the other markets, namely (Ghana, Nigeria, Kenya, Morocco, Tanzania, Tunisia and Zambia) do not have the potential to lag or lead.

Table 4
Wavelet multiple cross-correlations (WMCC).

Scale	Localisations	Time Lag (days)	Leading/Lagging variables	Localisations	Time Lag (days)	Leading/Lagging variables
	FULL SAMPLE			PRE COVID		
1	0.6033	0	Botswana	0.6137	0	Botswana
2	0.6335	0	Botswana	0.6418	0	Botswana
4	0.6713	0	South Africa	0.6978	0	Botswana
8	0.7298	0	South Africa	0.7373	0	Botswana
16	0.7618	−1.25	South Africa	0.7073	−1.25	South Africa
32	0.8087	1.25	Mauritius	0.6689	−5	South Africa
64	0.9035	−1.25	Mauritius	0.9280	6.25	Botswana
128	0.9952	−10	South Africa	0.9995	−10	South Africa
	DURING COVID			POST COVID		
1	0.6937	0	South Africa	0.6348	0	Botswana
2	0.6503	0	South Africa	0.6961	0	Botswana
4	0.8186	0	South Africa	0.6606	0	Botswana
8	0.9626	−1.25	South Africa	0.8413	0	Botswana
16	1.0000	10	Egypt	0.9279	0	Botswana
32	0	0	0	0.9998	3	Mauritius

The WMCC communicates the power of Botswana, South Africa, Mauritius and Egypt stock markets relative to the other markets. This could be attributed to their relatively high market capitalisation [17, [86]. While the Botswana and South African markets may have the potential to withstand challenges, they remain vulnerable to being the first to encounter shocks during turbulent times. This is an important factor that portfolio managers and investors should be aware of and take into consideration [17].

The WMCC findings indicate that stock markets of Botswana, South Africa and Mauritius seem to be the active market in terms of lead or lag the entire African stock market and as such highly susceptible to the impact of the COVID epidemic. The other markets even though may respond or react to the impact of the pandemic in relation with the entire market, their reaction is not significant. This finding reiterates that of [87] who found that the COVID epidemic had little influence on the pairwise correlation of the equity markets of Africa. Africa markets therefore continue to serve as reliable markets for diversification and risk management.

4.2. Renyi and shannon transfer entropy

We offer CEEMDAN Rényi and Shannon Transfer Entropy based estimates, along with the associated 95 % confidence intervals, to assess the information flow to African stocks across different intrinsic mode functions (IMFs). The IMFs indicate–short-medium-and long-term horizons which are used in this study to indicate information flow at different time horizons. The scales are interpreted as follows: IMFs 1–3, IMFs 4–6 and residual represent short, medium and long terms respectively [76]. Figs. 4 and 5 and Appendix 1 show the information flow between SSA stock returns and COVID.

From Fig. 4, there is evidence of significant negative information transmissions to Egypt, Morocco and Tunisia at IMF1, to Botswana at IMF2, Zimbabwe at IMF3, to Zambia and Ghana at IMF4 and to Egypt, Tunisia and Mauritius at IMF6. However, there is a positive transmission to Kenya at IMF1 and to Botswana at IMF6. The information flows become insignificant at IMF5. These results are from the Renyi's effective transfer entropy (RETE). According to the Shannon's effective transfer entropy (SETE), significant information flow is noticeable. For instance, at IMF1, there is significant positive information transmitted to Egypt, Kenya, Morocco and Zambia. At IMF2, IMF5, and IMF6, we have significant transmissions to Botswana, Tanzania and Botswana and Zimbabwe respectively.

The reception of negative ETEs in African equities markets implies that investing in these markets carries a significant level of risk in terms of returns on investment [88]. Investors would need to adjust their portfolio allocation in order to mitigate risk in response to the evolving market conditions [79]. Also, the unpredictable and significant information flow at different investment horizons supports the HMH. This hypothesis implies that market participants engage in a relentless search for competing risks and rewards, leading to competitiveness among selected stock returns [28]. In addition, information flow and spillover between markets reiterates the CMH [28].

Fig. 4 exhibits increase in negative flow of information to stock returns than positive transmissions (RETE). At IMF2 and IMF3, the information transmission is positive and towards Tunisia and South Africa respectively. From the series, we see negative transmissions from COVID to Tunisia, Morocco, Egypt, Ghana, Tanzania, Nigeria, South Africa, and Kenya at the various investment horizons.

On the right side of Fig. 5 is the result from the SETE. There are no significant negative transmissions to the stock market from COVID. Regardless, the multi-scales reveal significant positive transmissions to COVID as compared to the results on the left of Fig. 5. The flow post COVID may not have significant portfolio selection and management benefits. The COVID era may not have appreciable portfolio selection and management benefits.

4.3. Non-linear causality for robustness

The directional causality is interpreted as, changes in COVID is likely to cause changes in SSA stock markets and vice versa. This could be used to make some forecasts. Table 5 describes the causality test results between COVID and SSA stock market. We found a positive causal connection between COVID and the stock markets. The positive causal relation between COVID and the stock markets

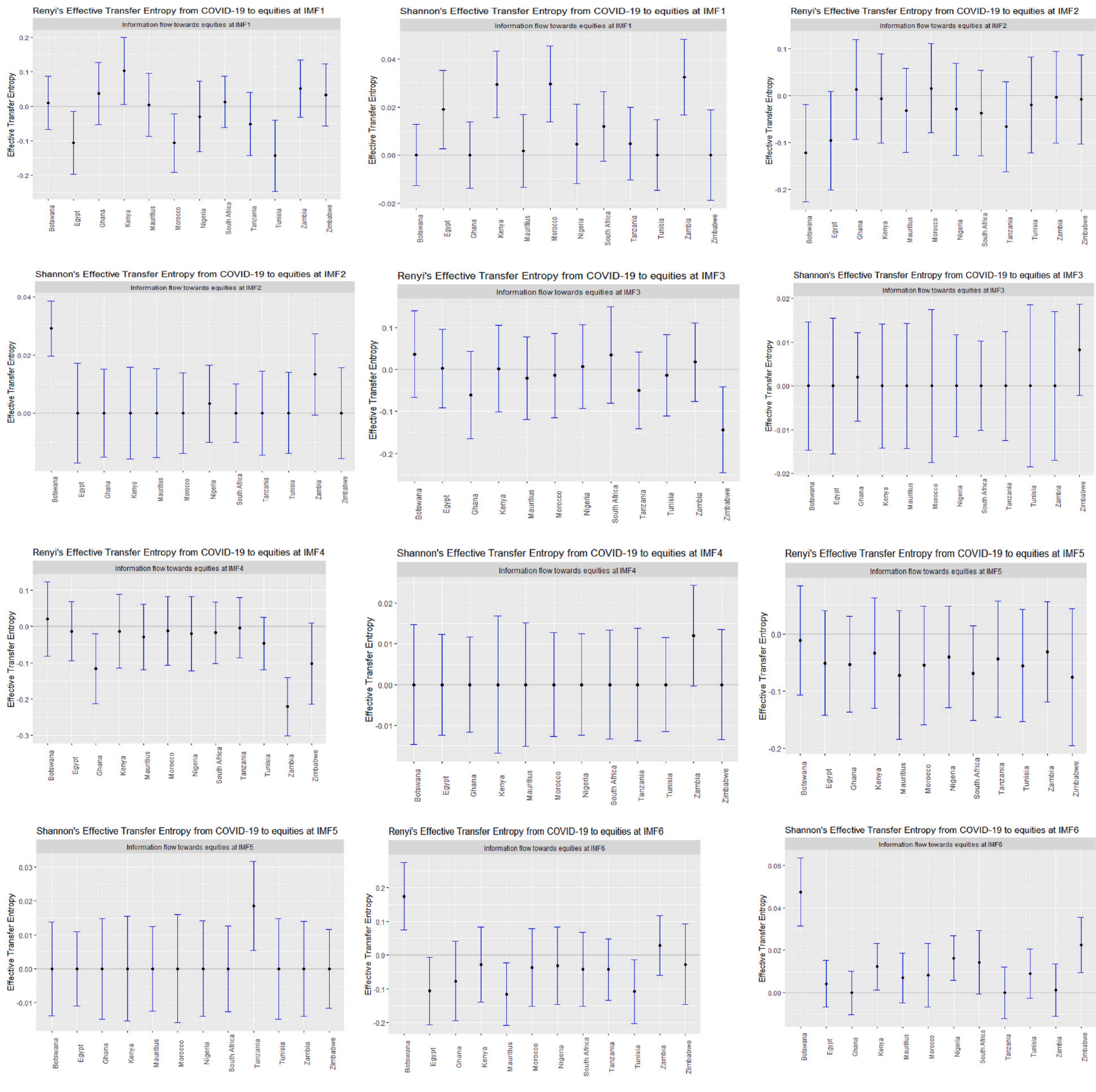

Fig. 4. Multi-scale information flow between SSA stock returns during COVID.

could be attributed to good uncertainty (or growth options). They contend that, this is the situation where an adverse event is characterised by the positive shifts in economic variables like consumption, outputs, and investments [89].

During the COVID period, evidence of causality from COVID to Egypt, Kenya, Mauritius, Morocco, South Africa, and Zimbabwe at 10 % significance level respectively was seen. During the post-COVID period, COVID has a positive predictive power for Kenya, Mauritius, and Zambia. It is evident that, the impact of COVID was felt more strongly during the pandemic than afterward. The strong impact of COVID during the pandemic era can be attributed to heightened uncertainty in economies as a result of the sudden COVID breakouts. This perspective is supported by research that show that uncertainty is response to a decline in economic activities [90]. The introduction of vaccinations, on the other hand, reduced uncertainty in the post-COVID era. This reflects the reduction in the causal impact of COVID during the post-COVID era analysis. Positive causal relationship from COVID to SSA stock markets were recorded for Egypt, Kenya, Mauritius, Morocco, South Africa, Zimbabwe, and Zambia. Second, the transfer entropy records positive transfers for Egypt, Botswana, Kenya, Morocco, South Africa, Tunisia, and Zambia. It is very clear that, Egypt, Kenya, Morocco, South Africa, and Zambia communicate power in both analyses. Further, the wavelet analysis showed that Botswana, South Africa, Mauritius, and Egypt stock markets demonstrated lead or lag potentials. Comparing the wavelet findings to the other two analysis, South Africa, Egypt, and Botswana also communicate power in the causal analysis, while South Africa, Egypt and Mauritius communicate power in the transfer

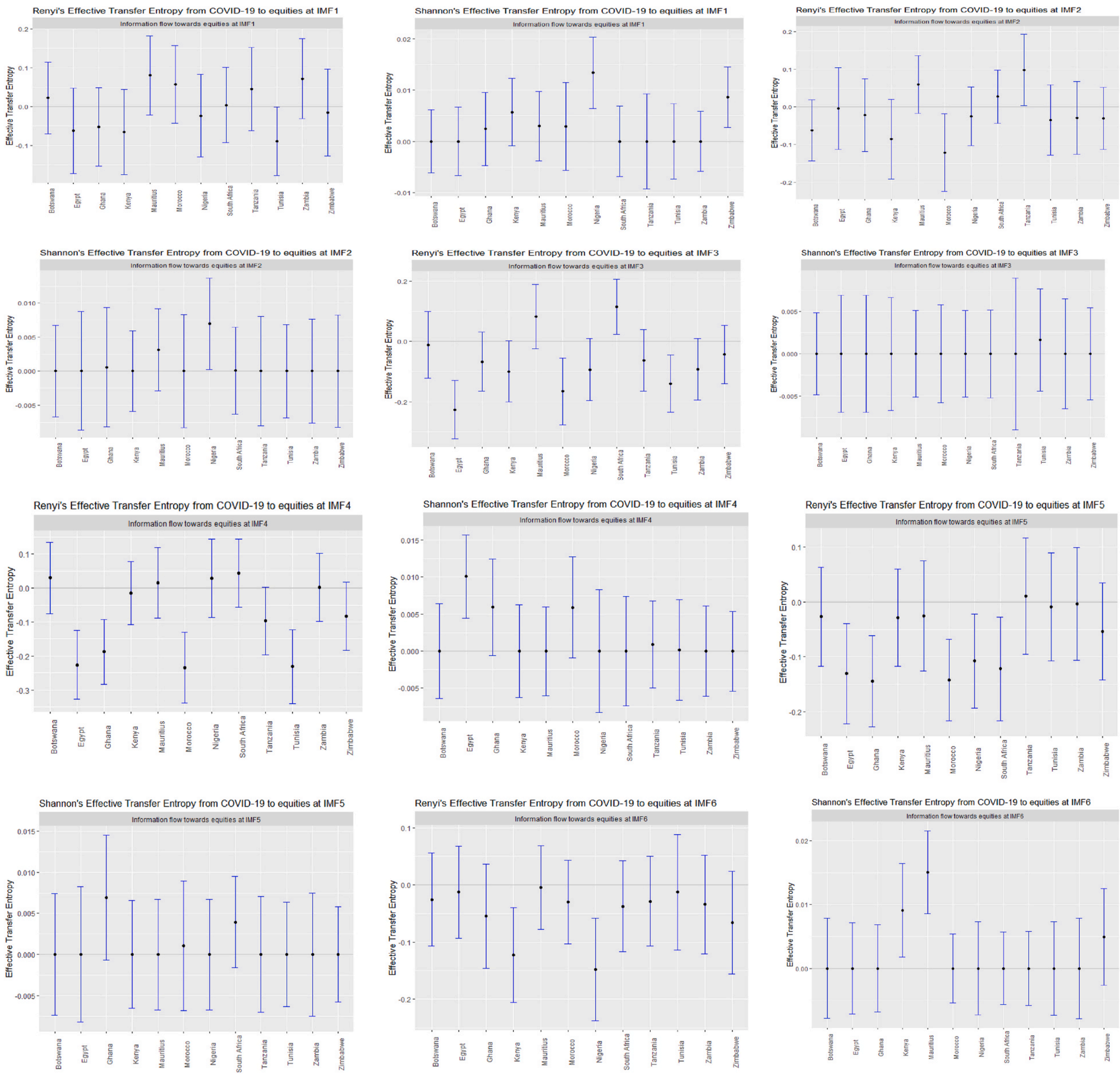

Fig. 5. Multi-scale information flow between SSA stock returns post-COVID.

entropy analyses. These similarities validate all of the different methodologies adopted in this study.

On the other uni-directional causal linkage, we find that, Egypt, Tanzania, and Zimbabwe have a positive predictive power over pandemic during the COVID era. This finding is similar to the Shannon effective transfer entropy which revealed positive transmissions to COVID. There was no causality evidence from SSA stock market to COVID during the Post-COVID era. Findings imply that some SSA stock markets have an impact on pandemic. We conclude that COVID is both a cause and effect of SSA stock markets.

5. Conclusion

To examine the co-movement between stock markets in Africa and information transmission among African stock markets as a result of the impact of COVID, this study departs from the conventional statistical models used in earlier studies by using WMC and WMCC. The paper additionally identified information transmission among African stock markets as a result of the COVID pandemic's havoc. In order to address this, the Renyi's and Shannon's ETE analyses of were employed. We discovered information flow to various stock markets, in the short-term time horizon (IMF1-IMF2), medium term horizon (IMF3-IMF4) and in the long-term horizon (IMF5-IMF6).

In Renyi's entropy, the likelihood of information transmission decreasing was high in the near future. A contrary trend emerged in

Table 5
Wavelet multiple cross-correlations (WMCC).

Direction	DURING COVID	POST-COVID
COVID ≠> Botswana	−0.034 (0.51357)	0.141 (0.44379)
COVID ≠> Egypt	**1.821(0.03433)***	−0.975 (0.83514)
COVID ≠> Ghana	1.071 (0.14217)	−0.442 (0.67079)
COVID ≠> Kenya	**1.514(0.06505)***	**1.347(0.08892)***
COVID ≠> Mauritius	**2.288(0.01107)***	**1.356(0.08760)***
COVID ≠> Morocco	**1.384(0.08311)***	0.382 (0.35138)
COVID ≠> Nigeria	0.400 (0.34450)	−1.197 (0.88434)
COVID ≠> South Africa	**1.626(0.05196)***	−1.494 (0.93247)
COVID ≠> Tanzania	−0.271 (0.60663)	−0.602 (0.72641)
COVID ≠> Tunisia	−0.497 (0.69033)	0.521 (0.30131)
COVID ≠> Zambia	−0.336 (0.63173)	**2.525(0.00579)**
COVID ≠> Zimbabwe	**2.100(0.01787)***	−0.886 (0.81222)
Botswana ≠> COVID	−0.248 (0.59812)	−0.503 (0.69242)
Egypt ≠> COVID	**1.458(0.07236)***	0.476 (0.68300)
Ghana ≠> COVID	0.005 (0.49789)	−0.738 (0.76979)
Kenya ≠> COVID	0.169 (0.43291)	0.158 (0.43738)
Mauritius ≠> COVID	0.611 (0.27064)	−0.107 (0.54254)
Morocco ≠> COVID	0.005 (0.49783)	0.860 (0.19483)
Nigeria ≠> COVID	1.070 (0.14226)	−0.175 (0.56963)
South Africa ≠> COVID	−0.106 (0.54225)	−0.506 (0.69374)
Tanzania ≠> COVID	**1.440(0.07490)***	1.025 (0.15264)
Tunisia ≠> COVID	−0.641 (0.73926)	−0.110 (0.54379)
Zambia ≠> COVID	−0.232 (0.59189)	0.192 (0.42382)
Zimbabwe ≠> COVID	**1.628(0.05172)***	−0.729 (0.76687)

the post-COVID period. Shannon's information flow decreased over time. The results from Renyi's effective transfer entropy generally indicate that negative information flows between African stock markets more frequently than positive information does, both during the COVID period and after. Under various time horizons, the Shannon's entropy registered non-negative information flow (IMF). This finding is not surprising since Shannon's entropy registers positive as long as there are no continuous cases. This suggests that while the outcomes from Shannon's entropy analysis were uni-directional, the findings from the Renyi's entropy for both eras were bi-directional.

Our findings generally show that information transmission/spill-overs predominate more in the short term within high frequency/spill-over than in the medium- and long-term horizons. In other words, the total spill-overs between African stock markets may have more to do with short-term, cyclical factors [86,91]. Only a few countries were identified as receiving information flow in both COVID and post-COVID era data. African markets are therefore probably not going to be affected by the COVID pandemic's shocks to the world's financial markets. These results corroborate observations of [92]. Only a few markets reacted/responded in the short term to information flow as a result of the havoc to global financial markets caused by the COVID pandemic. This generally indicates the inefficiency of African stock markets. A larger number of the markets under investigation exhibited no significant reaction/response to information flow. In general, the outcome does not support the EMH's claim that asset prices accurately reflect all relevant information in the short run [34].

Our findings indicate variations across time and frequencies, validating the adaptability, complexity, and heterogeneity of stock markets, as proffered by the AMH, CMH, and HMH [33,86,93,94]. This accentuates the suitability of the statistical approach employed in the study. The study found some markets such as Botswana, South Africa, Mauritius, and Egypt comes off as markets that responded to the pandemic in leads lags in the pre, during and post COVID era, and also reacting to information transmission even though the majority of the markets studied did not. It is therefore imperative for re-evaluating the widespread claim that African stock markets are less susceptible to contagion of stock market comovement, particularly during times of global uncertainties. This in some way supports the claims made by Ref. [7] that contagion occurs when there is a significant variation in the interconnectedness of markets following the occurrence of a shock in one market during periods of crises and uncertainties. This definition has been identified in notable studies on contagion among stock markets as a result of crises or uncertainties such as [9–12,48,95].

Investigating co-movement of stock markets in Africa, may have implications for theory, practice, and policy. Most studies assert that African stock markets can best be described as loosely integrated. There is co-movement between some African stock markets evidenced by the results. The results of this study suggest that some African markets such as Botswana, South Africa, Mauritius, and Egypt react or respond more strongly to information transmission than other markets. Thus, these markets could not be sheltered from the contagion effects of global nature as a result of the COVID pandemic. Our findings indicate that African stock prices exhibit time-varying non-homogeneous co-movements at higher frequency (shorter terms). The study generally corroborates the literature's claims that stock market co-movements intensify during times of uncertainties and decline after uncertainties. We contend that portfolio selection and diversification options may be more realistic for long-term investors than for short-term ones because of the apparent coherencies and lead-lag correlations occurring at greater frequencies. The results also allow for the deduction that the majority of African stock markets are insulated from the contagion effect of the pandemic, and as a result, foreign investors may feel secure diversifying their portfolio assets among African stocks without much worry. However, given that coherencies are primarily seen at higher frequency (shorter periods), this recommendation seems plausible for those with long-term investment views.

The implications of this study are crucial for African stock markets and policy makers in terms of implementation of strategies or policy solutions for the integration of fragmented stock markets and overcoming the challenges that confront Africa's financial markets integration agenda. We recommend to policymakers to consider the time and frequency characteristics of the various market indexes. Institutions and strategic investors should also consider the time and frequency dimensions of African stock market indices when pursuing a value maximization strategy, particularly during uncertain times like the COVID period because these uncertainties have the tendency to intensify co-movements, as shown in this study. This study focused on COVID 19 and African stocks. Future research could look at the same kind of study in other markets such as cryptocurrencies and commodity markets, while focusing on other global events such as the Russian-Ukraine war. Also, it is suggested that future studies should incorporate novel entropy features. Examples include dispersion entropy-based Lempel-Ziv complexity and particle swarm optimisation fractional slope entropy, which may offer enhanced distinguishing capabilities.

Ethical statement

Approval by an ethics committee was not needed for this study because secondary data used is available upon request.

Data availability statement

Data was obtained under license from EquityRT.

Additional information

No additional information is available for this article.

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CRediT authorship contribution statement

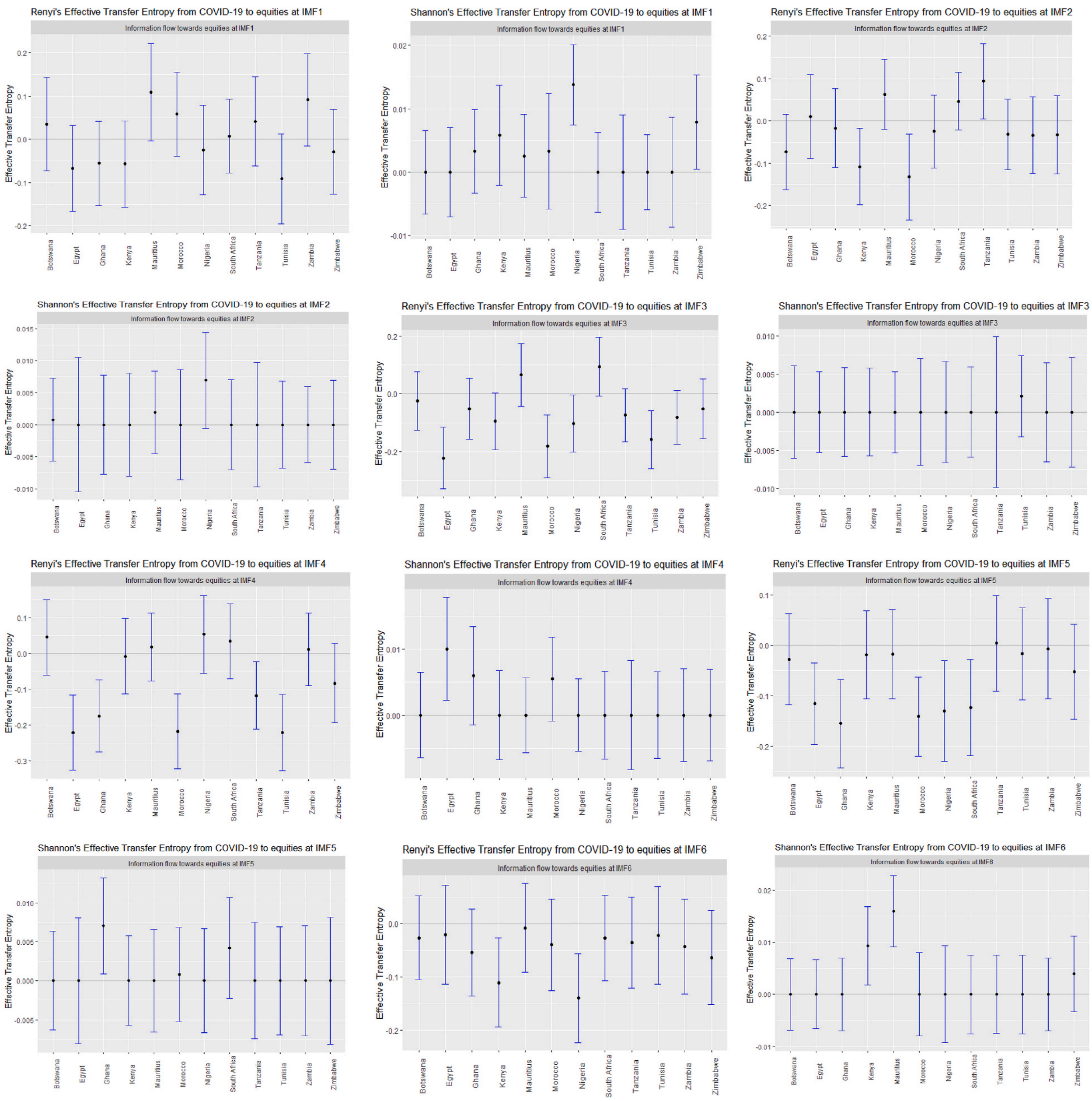
Peterson Owusu Junior: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Joseph Emmanuel Tetteh:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Bernice Nkrumah-Boadu:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Abigail N.K. Adjei:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors have no relevant financial or non-financial competing interests to disclose.

Appendix

Appendix 1
Multi-scale information flow between SSA stock returns post-COVID (Vaccination)



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