Received: 24 January 2022 | Accepted: 1 August 2022

DOI: 10.1111/infi.12419

ORIGINAL ARTICLE

International Finance WILEY

Stock market integration in Africa: Further evidence from an information-theoretic framework

Kingstone Nyakurukwa | **Yudhvir Seetharam**

School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa

Correspondence
Kingstone Nyakurukwa, School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa.
Email: knyakurukwa@gmail.com

Abstract

This study revisits stock market integration in Africa using an information-theoretic framework that quantifies the flow of information between exchanges. We use daily return data for seven MSCI-classified African stock exchanges between 2011 and 2021. As Bitcoin has become an important asset class on the African continent, we also explore whether this cryptocurrency confers any diversification benefits. Our method holds that stock markets are integrated if there is a significant flow of information between exchanges. The results reveal a statistically insignificant flow of information among African stock exchanges, and for the few cases in which information flow is statistically significant, the magnitudes are low. South Africa is the most influential stock market, as it transmits most of the total transfer entropy (informational value) in the system. We also observe that African stock exchanges are weakly integrated with Bitcoin.

KEYWORDS

Bitcoin, information theory, stock market integration, transfer entropy

1 | INTRODUCTION

The African Union Agenda 2063 is a blueprint toward transforming the continent to compete globally and deliver inclusive and sustainable development for African Union members. Since the inception of Africa's first continent-wide grouping, the Organisation of African Unity in 1963, various initiatives have been explored toward ensuring the creation of a fully fledged economic-integration framework on the continent. These initiatives (e.g., the 1979 Monrovia Summit, the 1980 Lagos Plan of Action, and the 1991 Abuja Treaty) have largely failed to produce economic integration (Hailu, 2015). Recently, the African Continental Free Trade Area (AfCFTA) was established and has brought renewed hope for a continent-wide economic-integration framework. However, Aniche (2020) discusses some concerns about AfCFTA, including low intra-African trade and infrastructure too weak to support seamless economic integration. Aniche (2020) proposes an initiative toward regional integration based on the establishment of a pan-African stock exchange capable of driving transnational mergers. However, the successful establishment of a pan-African stock exchange requires increased integration among African stock exchanges, as suggested by the creation of a Pan-European exchange, Euronext, in 2000 (Yepes-Rios et al., 2015). We, therefore, explore the state of stock market integration in Africa using the information theory of Shannon (1948) to determine the state of preparedness for a continental bourse.

African stock exchanges have undergone tremendous development in the past few years. These developments include the introduction of automated trades, demutualization of several African exchanges, introduction of derivative products in several countries, and introduction of Exchange Traded Funds and launch of US-dollar denominated trades, among other developments (Kunle & Omoruyi, 2014). The past few years have also seen some newly created exchanges and an increase in cross-listings within Africa. From only eight stock exchanges in 1989, the number of African stock exchanges has grown to 29, with representation in 38 countries (Solyman, 2017). However, despite these markets becoming comparatively deeper and more sophisticated, they remain segmented from international markets and weakly integrated within the continent (Kumah & Odei-Mensah, 2021).

Several sources of stock market integration have been documented in the literature. Karim and Majid (2010) report findings that articulate the importance of trade and geographic proximity as drivers of stock market integration. Bracker et al. (1999) attribute the extent of integration across international capital markets directly to the degree of the economic integration of the underlying countries. Stock market characteristics may also play a role in determining the extent of integration among stock markets (Dorodnykh, 2014). These characteristics, such as stock market size, common industry constituents, and levels of liquidity, may determine the stage of development of a stock market. Stock markets that have similar size, liquidity, and trading-related costs may be at the same stage of development and may therefore exhibit greater integration (Nyakurukwa, 2021).

According to Collins and Biekpe (2003), a market that is financially integrated with other markets may have better access to large pools of potential investors. This can have a downward effect on the cost of equity, which can help increase the viability of projects. Ultimately, the effect will spill over to the macro-economy, as this will translate into increased economic growth and reduced unemployment. The downside of increased integration among markets is that markets become more sensitive to global economic events.

Several studies examine the extent of stock market integration in Africa. Some take a bilateral approach to determine the extent of integration between two exchanges, while others use a regional approach, and a few implement a continent-wide approach. These studies show heterogeneity in the sample periods used as well as the sampled countries. Most studies that take a continent-wide approach include the countries hosting the major African exchanges, including South Africa, Nigeria, Egypt, Tunisia, Morocco and Kenya (e.g., Agyei-Ampomah, 2011), while others also include peripheral exchanges like those in Zambia and Malawi (e.g., Bundoo, 2017). The present study includes seven Morgan Stanley Capital International (MSCI)—classified countries with adequate time series data (South Africa, Egypt, Nigeria, Morocco, Kenya, Tunisia and Botswana). Since some African investors are also turning to cryptocurrency as an important asset class for diversification purposes, we consider how crypto assets are related to African equity markets. As the African continent pushes for increased economic and stock market integration among members, cryptocurrencies are thought to have the potential to enable faster and cheaper cross-border transactions, thereby facilitating trade. Thus, trade among African countries is expected to increase with the adoption of digital currencies, leading to increased economic and stock market integration. Among cryptocurrencies, Bitcoin is the most used in Africa. Statistics show that Kenya, South Africa and Nigeria are ranked in the top 10 countries globally in terms of cryptocurrency interest.[1] For this reason, we examine how Bitcoin is related to African stock markets and whether it provides avenues for portfolio diversification.

Empirically, in most studies on the linkages among African stock exchanges, South Africa has been reported to have close links with the developed markets while it is weakly integrated with other African countries. Agyei-Ampomah (2011) investigates the integration of stock markets in Africa and reports that African stock markets are segmented from global markets, with the exception of South Africa. Agyei-Ampomah (2011) reports that even within the same regional economic blocs, correlations are low and sometimes negative. Alagidede (2009), in a study investigating comovement among the most developed exchanges of Africa, finds that African exchanges are not influenced by each other despite increased efforts from various economic reforms and financial liberalization. Alagidede (2009) rather points to the irrelevance of geographic and economic ties in the integration of the African market. Atenya (2019) examines the flow of information between the Johannesburg Stock Exchange (JSE) and the East African exchanges of Uganda, Tanzania, Kenya and Rwanda. Using a data set of stock index prices of the five countries between 17 January 2008 and 31 March 2017, this study finds no evidence of the JSE influencing the returns of the East African exchanges.

With the increasing use of cryptocurrency in Africa, Kumah and Odei-Mensah (2021) investigate the linkages between three base cryptocurrencies (Bitcoin, Ethereum and Litecoin) and eight African stock exchanges (Egypt, South Africa, Nigeria, Mauritius, Kenya, Ghana, Tunisia and Morocco). The study uses a sample period between 2015 and 2019 to untangle the connectedness of cryptocurrencies and stock exchanges in a time-frequency domain. The study concludes that cryptocurrencies offer diversification benefits for African stock exchanges. Our study differs from Kumah and Odei-Mensah (2021) in that we apply the information theory of Shannon (1948) to determine integration between Bitcoin and African stock exchanges and we use a longer sample period that also encompasses the COVID-19 period.

Differing and sometimes innovative approaches have been used to untangle and determine dependencies among African stock exchanges. While some studies use traditional VAR-based and Pearson correlation analyses, recent studies counter the inadequacies of these traditional methods by using, among other methods, the BEKK-GARCH model (Emenike, 2021); Toda and Yamamoto Granger causality (Obadiaru et al., 2020); wavelet multiple correlation (WMC) and wavelet multiple cross-correlation (Boako & Alagidede, 2017; Tweneboah et al., 2019); and copulas (Mensah & Alagidede, 2017). Most of these studies conclude that African stock exchanges are weakly integrated and are largely segmented from developed exchanges. Though some studies show improved WMCs at lower frequencies (e.g., Tweneboah et al., 2019), the correlations are still low compared to other regions, such as Asia (Tiwari et al., 2013) and the Eurozone (Fernández-Macho, 2012). We extend existing empirical studies by utilizing an alternative framework (information theory) that accurately quantifies and shows the direction of information flow between random variables. The thrust of information theory is understanding the transmission, processing, extraction and utilization of information. We utilize transfer entropy (informational value) to determine the magnitude and direction of the information flow between stock markets by treating stock markets as a complex system.

Our study adds to the literature on stock market integration in Africa in several ways. First, our sample period includes the COVID-19 period, allowing examination of the effect of "black swan" events on African stock market integration. Second, to the best of our knowledge, this is the first study to apply information theory to untangle the state of African stock market integration. Third, with increased use of cryptocurrency as an asset class in African markets, we examine the information flow between African stock exchanges and Bitcoin, the most used cryptocurrency in Africa. Our results show that African stock markets remain weakly integrated, as the flow of information between markets is quite low in absolute terms and insignificant at any conventional level of statistical significance in most cases. As for cryptocurrency, there is an insignificant flow of information from all equities to Bitcoin for all subperiods. However, in the COVID period, we report a significant flow of information from Bitcoin to stock indices for Nigeria, Kenya and South Africa, the countries with the largest volume of Bitcoin usage in Africa (though the magnitudes are low). The findings from this study are important to the international investor, as there is evidence of potential portfolio diversification across different African markets. The increased linkages between African equities in the COVID-19 period provide more reason as to why cryptocurrencies should be regulated to prevent crashes originating in crypto markets from spilling into equity markets. Our results also point to the need for more to be done to ensure the integration of African stock markets before a continental bourse is launched.

This study proceeds as follows. Section 2 outlines our methodology. Section 3 presents our results and a discussion thereof. Finally, Section 4 sets forth our conclusions.

2 | METHODOLOGY

2.1 | Data and variables

To determine which African stock exchanges to include in this study, we depend on the MSCI Annual Market Classification of Stock Exchanges Review for 2021. Every year, MSCI evaluates stock exchanges around the world and classifies each as a developed, emerging, frontier, or standalone market. The 2021 evaluation report of the world stock exchanges features nine African countries classified across the MSCI standard classifications (MSCI, 2022). The classification of these stock exchanges is shown in Table 1.

From the classified African stock exchanges shown in Table 1, Mauritius, WAEMU and Zimbabwe are excluded from analysis because of insufficient data points compared to other countries, as this study uses time-based analysis. The following African stock exchanges are thus included in this study: South Africa, Egypt, Kenya, Morocco, Nigeria, Tunisia and Botswana. We also explore the integration of African stock exchanges with cryptocurrency. Since there are multiple cryptocurrencies in use worldwide, we sought the cryptocurrency that is most common in Africa. According to official statistics, in 2020, interest in Bitcoin was higher

TABLE 1 List of MSCI African classified stock exchanges

Emerging markets	Frontier markets	Standalone markets
South Africa (MXZA)	Kenya (MXKE)	Botswana (MXBW)
Egypt (MXEG)	Mauritius (MXMY)	Zimbabwe (MXZW)
	Morocco (MXMA)	
	Nigeria (MXNI)	
	Tunisia (MXTN)	
	WAEMU* (MXWAEMU)	

Note: WAEMU is the West African Economic and Monetary Union. The codes in parentheses are those used by Bloomberg for each stock index and these are used henceforth.

in Africa and Latin America than in some developed economies (de Best, 2022). For example, $400 million US dollars' worth of Nigerian Naira was used to buy Bitcoin on an exchange in 2020, making Bitcoin trading volume in Nigeria twice as high as in the Eurozone (de Best, 2021). The 2020 statistics also show that Kenya and South Africa were number 7 and 8 out of 44, respectively, for countries with the most Bitcoin traded. Kenya and South Africa, respectively, used $91 million and $87 million US dollars' worth of Kenyan shillings and South African rand for Bitcoin purchases on online exchanges (de Best, 2021). Following Tiwari et al. (2013), to address missing data due to different public holidays in African stock markets, some daily observations were deleted. Our sample period runs from the 1st of September 2011 to the 11th of November 2021. After matching the daily observations among the seven equity indices and Bitcoin closing prices, there were 2961 observations. Data for the MSCI indices were sourced from Bloomberg.

We use MSCI global indices as benchmarks for each respective market. MSCI global indices provide a fairer indication of market performance compared to standard indices, as they are computed by the same provider, thereby alleviating potential measurement errors. For Bitcoin, we use daily closing prices of the cryptocurrency as provided by https://www.investing.com/. We use log returns to describe a financial time series, as follows:

$$x_n \equiv \ln(S_n) - \ln(S_{n-1}), \tag{1}$$

where S_n stands for the closing prices of the MSCI indexes and Bitcoin on the nth trading day.

2.2 | Econometric model

2.2.1 | Transfer entropy

Transfer entropy is a nonparametric measure of directed, asymmetric information transfer between two-time series processes and does not assume subject-specific restrictions concerning underlying stochastic processes. Assuming that log denotes the logarithm of a number to base 2, Shannon entropy (Shannon, 1948) postulates that for a discrete random variable J with probability distribution $p(j)$, where j stands for the various outcomes J can take, the average number of bits required to encode the independent draws from the distribution of J optimally can be calculated as:

$$H_J = -\Sigma p(j).\ \log. \tag{2}$$

Effectively, Equation (2) measures the uncertainty which increases with the number of bits needed to optimally encode a sequence of realizations of J. Measurement of the flow of information between two time series is done by combining the concept of Shannon entropy with the concept of Kullback–Liebler distance (Kullback & Leibler, 1951) coupled with an assumption that the underlying process evolves over time through a Markov process (Schreiber, 2000). Allowing $I \wedge J$ to denote two discrete random variables with marginal probability distributions $p(i)$ and $p(j)$, respectively, as well as a joint distribution $p(i, j)$ whose dynamic structures correspond to stationary Markov processes of order $k \wedge j$, the Markov property implies that the probability of observing I at time $t + 1$ in state i conditional on the k previous observations is

$$p(i_{t+1}|i_t, ..., i_{t-k+1}) = p(i_{t+1} \vee i_t, ..., i_{t-k}). \tag{3}$$

The average number of bits needed to encode the observation in $t + 1$ if the previous k values are known is given by

$$h_1(k) = -\Sigma p\left(i_{t+1}, i_t^{(k)}\right).\ \log, \tag{4}$$

where $i_t^{(k)} = (i_t, ..., i_{t-k+1})$. $h_j(l)$ is derived analogously for process J. In a bivariate specification, the flow of information from one process (J) to another process (I) is calculated by finding the departure from the generalized Markov property $p\left(i_{t+1}|i_t^{(k)}\right) = p\left(i_{t+1}|i_t^{(k)}, j_t^{(l)}\right)$ using the Kullback–Liebler distance (Schreiber, 2000). Shannon transfer entropy is computed using the following formula:

$$T_{J\to I}(k, l) = \sum_{i,j} p\left(i_{t+1}, i_t^{(k)}, j_t^{(l)}\right).\ \log\left(\frac{p\left(i_{t+1}\middle|i_t^{(k)}, j_t^{(l)}\right)}{p\left(i_{t+1}\middle|i_t^{(k)}\right)}\right), \tag{5}$$

where $T_{J\to I}$ measures the flow of information from one process J to another process I. ($T_{I\to J}$ measures the flow of information from I to J and can be derived analogously).

The transfer entropy represented by Equation (5) can produce biased estimates because of small sample effects. This is ameliorated by the use of effective transfer entropy proposed by Marschinski and Kantz (2002) and is computed as follows:

$$ET_{J\to I}(k, l) = T_{J\to I} - T_{J\text{shuffled}\to I}(k, l), \tag{6}$$

where $T_{J\text{shuffled}\to I}(k, l)$ indicates transfer entropy using a shuffled version of the time series of J. Shuffling, in this case, involves drawing values from the time series of J at random and realigning them to generate a new series. The process of shuffling extinguishes the time series dependencies of J and the statistical dependencies between $I \wedge J$. Consequently, $T_{J\text{shuffled}\to I}(k, l)$ converges to zero with increasing sample size, and any nonzero value of $T_{J\text{shuffled}\to I}(k, l)$ is due to the small sample size. A consistent estimator is therefore attained by repeated shuffling and subsequently averaging the transfer entropy estimates across all replications. This average is subtracted from the Shannon transfer entropy estimates to obtain effective transfer entropy estimates which are bias-corrected. The statistical significance of the transfer entropy estimates is derived using a Markov block bootstrap proposed by Dimpfl and Peter (2013) which maintains the dependencies within the time series, contrary to the shuffling process outlined above. The Markov block bootstrap generates the distribution of transfer entropy estimates under the null hypothesis of no information. Shannonian transfer is then estimated using the simulated time series. This process is repeated, thereby yielding a distribution of the entropy transfer estimate under the null hypothesis of no information flow. The p value associated with the null hypothesis of no information transfer is given by $1 - \hat{q}_{TE}$, where $\hat{q}_{TE}$ denotes the quantile of the simulated distribution that corresponds to the original transfer entropy estimate.

Note that the calculation of Shannonian entropy is based on discrete data. Because this study uses continuous index returns, these data are discretized using symbolic coding. This is achieved by partitioning the data into a finite number of bins based on quantiles of the empirical distribution of the data. Assuming the bounds specified for the n bins are represented by $q_{1,}q_2, \ldots, q_n$, where $q_1 < q_2 \ldots < q_n$, and assuming that a time series is denoted by y_t, the data are recoded by:

$$\begin{cases} 1 & \text{for } y_t \le q_1 \\ 2 & \text{for } q_1 < y_t \le q_2 \\ \vdots & \vdots \\ n-1 & \text{for } q_{n-1} < y_t \le q_2 \\ n & \text{for } y_t \ge q_n \end{cases}$$

Each value in the time series y_t is replaced with an integer $(1,2, \ldots, n)$ according to how S_t relates to the interval specified by the lower and upper bounds $q_1 q_n$. The choice of bins is justified by the empirical distribution of the data.

2.2.2 | Bivariate wavelet correlation and WMC

Several studies use WMC to determine dependencies among stock exchanges. We utilize WMC as a robustness check to determine whether our results are consistent with the information-theoretic framework. Wavelet correlation is approximated via construction of variances and covariances of time series at different wavelet scales. The wavelet variance of a stochastic process is estimated using maximal overlap discrete wavelet transform (MODWT) coefficients for scale $\tau_j = 2^{j-1}$ through:

$$\hat{\sigma}_x^2(\tau_j) = \frac{1}{\hat{N}_j} \sum_{k=L_j-1}^{N-1} (\hat{W}_{j,k})^2, \tag{7}$$

where $\hat{W}_{j,k}$ is the MODWT wavelet coefficient of variable X at scale τ_j;

$\hat{N}_j$ is the number of coefficients that are unaffected by the boundary; and

L_j is the length of the scale τ_j wavelet filter.

Decomposition of the covariances between pairs of stochastic processes is done on a scale-by-scale basis. The wavelet covariance at scale τ_j is represented by:

$$\gamma_{XY}(\tau_j) = \text{cov}_{XY}(\tau_j) = \frac{1}{\hat{N}_j} \sum_{k=L_j-1}^{N-1} \hat{W}_{j,k}^{x} \hat{W}_{j,k}^{y}. \tag{8}$$

With a wavelet covariance for (x_t, y_t) and wavelet variances for (x_t) and (y_t), the MODWT approximation of the wavelet correlation is given by:

$$\hat{\rho}_{xy}(\tau_j) = \frac{\text{Cov}_{xy}(\tau_j)}{\hat{\sigma}_x^2(\tau_j)\hat{\sigma}_y^2(\tau_j)}. \tag{9}$$

The bivariate wavelet correlation described above is criticized due to several limitations, and the WMC suggested by Fernández-Macho (2012) has been proffered as more succinct. Given that a multivariate stochastic process is given by $X_t = (x_{1t}, x_{2t}, ..., x_{mt})$ and that the respective scale λ_j is represented by $W_{jt} = (w_{1jt,}w_{2jt}, ..., w_{njt})$, the wavelet coefficients can be estimated by applying MODWT to each x_{it} process. The WMC is estimated as follows:

$$\varphi_X(\lambda_j) = \sqrt{1 - \frac{1}{\text{maxdiag}\, P_j^{-1}}}, \tag{10}$$

where P_j refers to the $n \times n$ correlation matrix of W_{jt} and the max diag (.) operator provides selection for the largest element in the diagonal of the argument.

3 | RESULTS AND DISCUSSION

3.1 | Summary statistics

This section presents the results of our analyses. First, descriptive statistics are presented in Table 2 and visualization of the MSCI return indices and Bitcoin returns for the sampled companies are shown in Figure 1.

Table 2 shows that Bitcoin has the highest maximum return, the lowest minimum return and the highest standard deviation of returns, confirming the widely held belief that cryptocurrency is more volatile than equity markets. From Figure 1, the MSCI return series for the African stock exchanges and Bitcoin show volatility clustering, a well-known stylized fact of financial time series. The effect of the COVID-19 pandemic on the African stock exchanges can be seen immediately from the sharp slump in the return series for all indices around March 2020, when COVID-19 was declared a global pandemic by the World Health Organisation (Obeng-Odoom, 2020). Table 3 shows the Pearson correlation matrix of the variables.

As shown in Table 3, all Pearson correlation coefficients are low, with most of them negative, giving elementary evidence of weak linkages among the stock markets. Except for Botswana, all the countries have exchanges that are negatively correlated with Bitcoin. This shows the possibility of diversification benefits from investing in African exchanges and Bitcoin. We use robust econometric models to explore these possibilities in the following sections.

TABLE 2 Summary statistics of equity and Bitcoin returns

Ticker	Mean	Median	Max	Min	SD
MXZA	0.0002	0.0000	0.0722	−0.0947	0.0117
MXEG	0.0003	0.0000	0.1296	−0.1781	0.0152
MXKE	0.0004	0.0001	0.0483	−0.0698	0.0099
MXMA	−0.0001	0.0000	0.0542	−0.1030	0.0082
MXNI	0.0000	0.0000	0.0847	−0.0747	0.0114
MXTN	0.0002	0.0000	0.0467	−0.0474	0.0078
MXBW	−0.0004	0.0000	0.1541	−0.2112	0.0120
BTC	0.0038	0.0000	1.4741	−0.8488	0.0693

Note: Ticker codes are as defined in Table 1. Statistics are rounded off to four decimal places. Max, Min and SD represent maximum value, minimum value and standard deviation, respectively.

3.2 | Transfer entropy

We calculate pairwise transfer entropy among all indices considered and construct a matrix such that each value in the position $(i. j)$ will contain the value of transfer entropy from ticker $[i]$ to ticker $[j]$, as presented in Table 4.

We normalize the transfer entropy values by dividing them by the maximum value in the matrix such that all values range from 0 to 1. In Table 4, the information flow from X (represented by the vertical axis of the table) to Y (represented by the horizontal axis of the table) is shown in grey. For example using Panel A of Table 4, the magnitudes of information flow from MXZA to MXEG and MXKE are 0.4680 and 0.2933, respectively. On the other hand, the flow of information from Y to X is shown in white; for example, the magnitudes of information flow from MXZA to MXEG and MXKE are 0.0361 and 0.2345, respectively. Several facts can be deduced in the transfer entropy matrix in Table 4. First, for the full sample, the highest magnitude of information flows from MXZA to MXEG (0.0046); this shows weak integration between the most integrated markets in Africa. The rest of the pairwise magnitudes of information flow in either direction for the full sample are all close to zero, showing that African stock exchanges are weakly integrated. When the full sample is split into the pre-COVID[2] period and the COVID subsamples, the pattern remains the same for the former, while the latter shows the highest magnitude of information flowing from MXEG to MXTN. However, even in the COVID-19 period, the largest magnitude of information flow in the matrix (0.034) is still too low compared to the maximum value of 1 expected for perfectly correlated markets. The marginal increase in information flow from Egypt to Tunisia during the COVID period is not surprising since these countries are in the same geographic region.

We also calculate the marginal contribution of each market to the total transfer entropy in the system by calculating the sum of transfer entropy for each row in the transfer entropy matrix, which we also normalize such that all values range from 0 to 1. The results from this procedure are shown in Panel D of Table 4. We observe that for the full sample and the pre-COVID subsample, South Africa and Egypt are the most influential markets, in that order. In the full sample, South Africa and Egypt each retain 27.81% and 18.90% of total transfer entropy, respectively, while for the pre-COVID subsample, the two countries retain 31.19% and 23.43%, respectively. The pattern changes in the COVID-19 period as Tunisia becomes the most influential market, retaining 31.88%

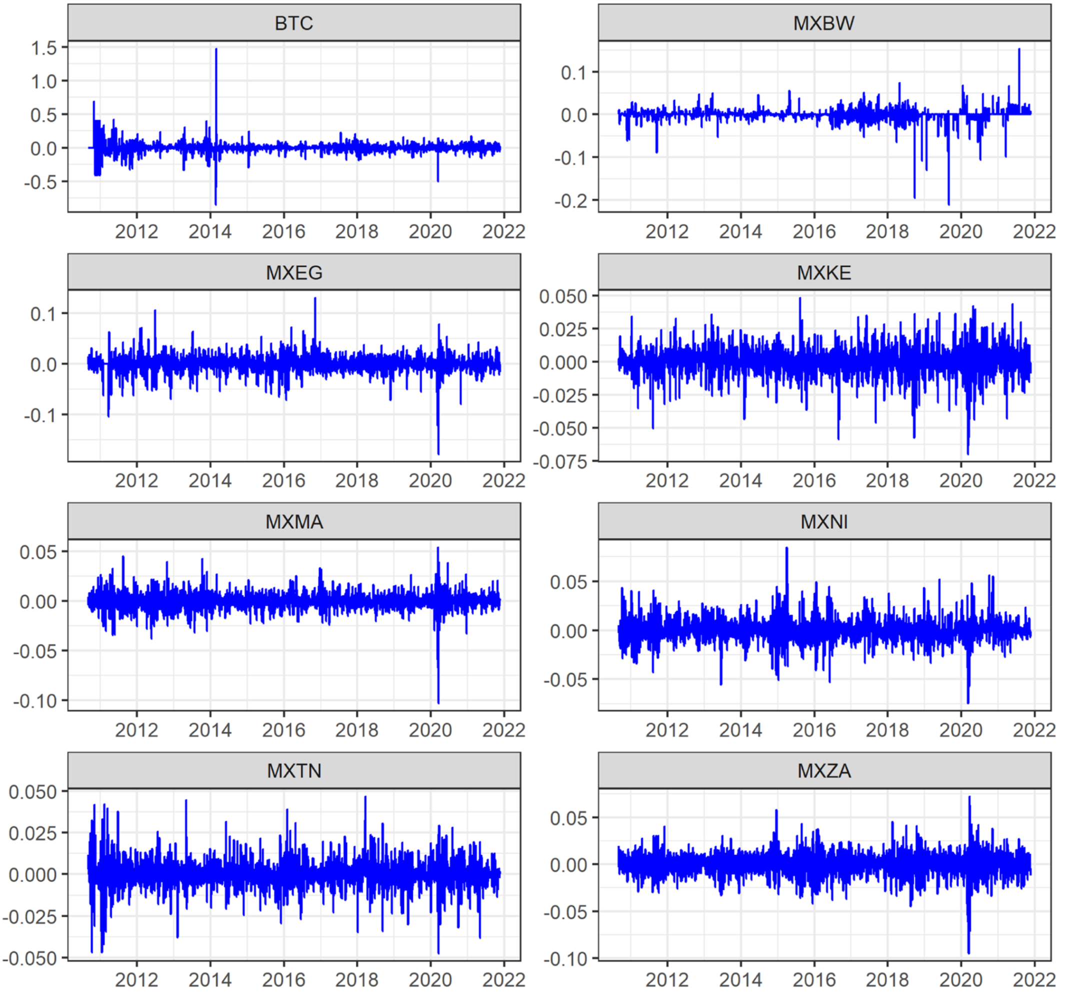

FIGURE 1 Visualization of equity and Bitcoin returns. The ticker codes represent equities as defined in Table 1. [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Pearson correlation matrix of equities and Bitcoin

	BTC	MXZA	MXEG	MXKE	MXMA	MXNI	MXTN	MXBW
BTC	1.0000							
MXZA	−0.0410**	1.0000						
MXEG	−0.0330*	0.1007***	1.0000					
MXKE	−0.0001	0.0615***	0.0583***	1.0000				
MXMA	−0.0172	0.1077***	0.1312	0.0787***	1.0000			
MXNI	0.0473***	0.0618***	0.0630***	0.1543***	0.0414**	1.0000		
MXTN	−0.0610***	0.0236	0.0193***	0.0175	0.0416**	0.0083	1.0000	
MXBW	0.0120	−0.0034	−0.0266	0.0189	0.0002	−0.0072	−0.0188	1.0000

Note: The ticker symbols are as defined in Table 1. *, ** and *** represent statistical significance at the 10%, 5% and 1% levels, respectively.

TABLE 4 Pairwise transfer entropies for sampled indices

		Flow of information from Y to X							
		Y							
		Panel A: Full sample							
			MXZA	MXEG	MXKE	MXMA	MXNI	MXTN	MXBW
Flow of information from X to Y	X	MXZA	0.0000	0.4680	0.2933	0.1816	0.0699	0.0000	0.0000
		MXEG	0.0361	0.0000	0.0564	0.0000	0.8396	0.0000	0.0955
		MXKE	0.2345	0.1084	0.0000	0.0866	0.0246	0.0415	0.0709
		MXMA	0.2228	0.0655	0.0131	0.0000	0.1155	0.0000	0.0000
		MXNI	0.2425	0.1910	0.1892	0.0000	0.0000	0.0000	0.1334
		MXTN	0.2680	0.0300	0.0150	0.1058	0.0955	0.0000	0.0000
		MXBW	0.0838	0.1456	0.0894	0.0699	0.0000	0.1588	0.0000
		Panel B: Pre-COVID samples							
		MXZA	0.0000	0.4015	0.2103	0.0864	0.6473	0.0597	0.0000
		MXEG	0.0506	0.0000	0.1376	0.0000	0.7543	0.0000	0.1563
		MXKE	0.0000	0.0438	0.0000	0.0036	0.0000	0.0000	0.0000
		MXMA	0.1863	0.0000	0.0000	0.0000	0.2027	0.0000	0.0000
		MXNI	0.3496	0.0658	0.1499	0.0000	0.0000	0.0914	0.0391
		MXTN	0.2594	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		MXBW	0.1505	0.0152	0.26261	0.0622	0.0000	0.1914	0.0000
		Panel C: COVID samples							
		MXZA	0.0000	2.3526	0.5274	0.4130	0.8020	0.2464	0.0000
		MXEG	1.6873	0.0000	0.0200	1.9705	0.0495	0.0778	0.0000
		MXKE	0.2979	0.8254	0.0000	2.0441	0.0000	0.2532	0.0000
		MXMA	0.9306	0.6856	0.0000	0.0000	0.0000	0.0505	0.0000
		MXNI	0.5669	0.0000	2.9943	1.2113	0.0000	0.8460	0.0000
		MXTN	0.5275	3.3483	0.3042	2.6267	2.3156	0.0000	0.0000
		MXBW	0.0000	0.5476	0.0000	0.0000	0.2770	0.0000	0.0000
		Panel D: Marginal contribution to Total Entropy							
		Full sample	0.2780	0.1890	0.1101	0.0912	0.1357	0.0924	0.1031
		Pre-COVID	0.3118	0.2342	0.0056	0.0843	0.1589	0.0534	0.1513
		COVID	0.1519	0.1280	0.1188	0.0517	0.2016	0.3187	0.0290

Note: Entropy values in Panels A, B and C are multiplied by 100 for readability. The ticker symbols are as defined in Table 1.

of total transfer entropy, followed by Nigeria, which retains 20.16% of normalized transfer entropy. These results mostly corroborate earlier studies on stock market integration in Africa which show South Africa leading other markets (Boamah, 2016). Also, note that information flow among African stock markets marginally increased after COVID-19 began, as demonstrated by the larger magnitudes of transfer entropy in Panel C compared to Panel B. This is in line with Lehkonen (2015), who reports a marginal increase in stock market integration among less developed stock markets following the Global Financial Crisis.

As mentioned earlier, Bitcoin has become an important asset class in Africa, as demonstrated by the dominance of African countries among the top countries investing in cryptocurrency. Figure 2 shows the results for the effective transfer entropies of African stock indices to and from Bitcoin. As before, the sample period is divided into the full sample, the pre-COVID subsample and the COVID subsample.

A notable pattern in Figure 2 is that for all subsamples (full sample, pre-COVID and COVID, shown in Panels A, B and C, respectively), there is no significant flow of information from African equity indices to Bitcoin. Conversely, South Africa, Nigeria and Kenya experience

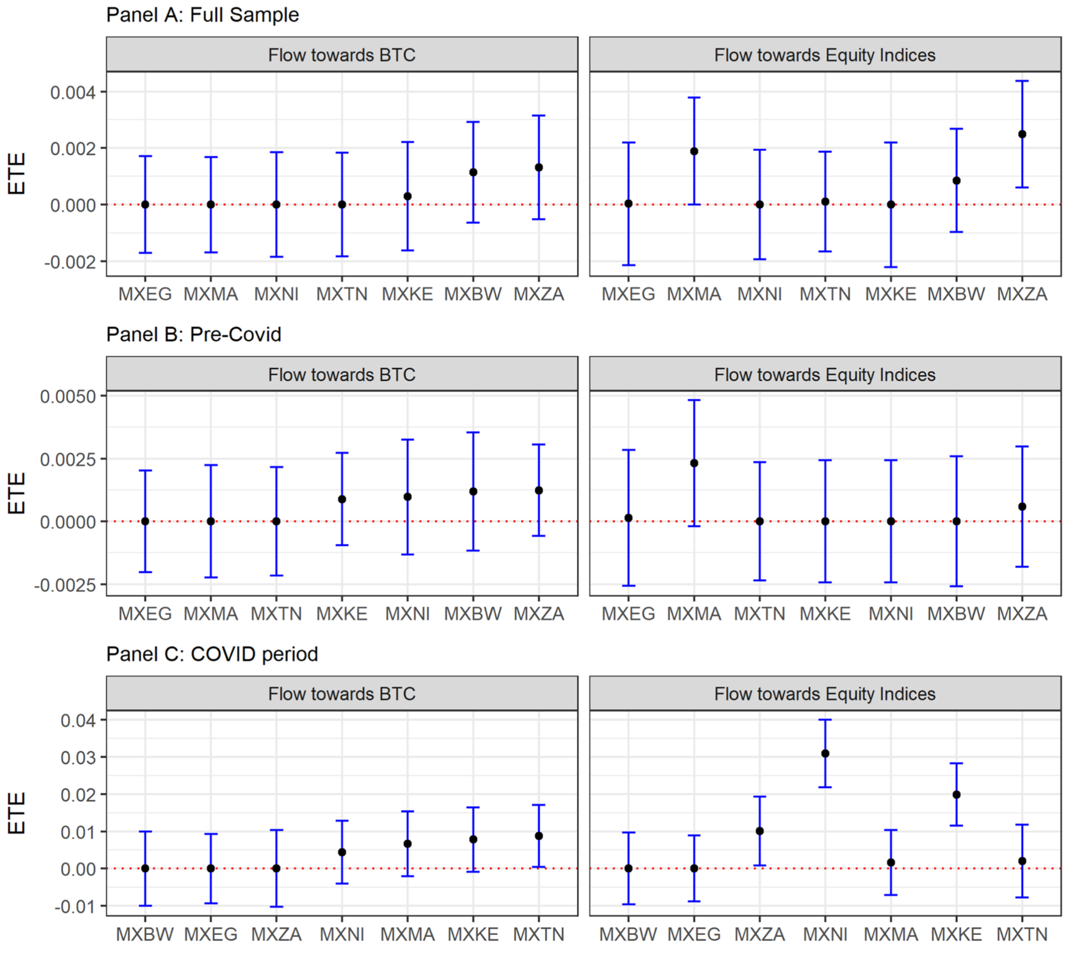

FIGURE 2 Information flow between equities and Bitcoin before and during COVID-19. This figure shows Shannonian effective transfer entropy (ETE) estimates together with 95% confidence bounds for all indices. Both ends of each blue line segment enclose ETE within 95% confidence bounds. A lower end of the line below zero ETE indicates insignificant information flow from either direction at the 5% level of significance. The ticker symbols are as defined in Table 1. [Color figure can be viewed at wileyonlinelibrary.com]

a significant flow of information from Bitcoin to equity indices during the COVID period. Thus, for investors who invest in equities and Bitcoin in these three countries, the diversification benefits decrease in a crisis, as shown by the significant flow of information during the COVID period (Panel C). However, the significant transfer entropies for these two countries in the COVID period remain too low in absolute terms (0.01 for South Africa, 0.03 for Nigeria and 0.02 for Kenya) as perfect information flow between markets is expected to be close to 1. In the pre-COVID period, none of these countries experiences a significant flow of information in the same direction. Interestingly, Nigeria, South Africa and Kenya have some of the top investors in Bitcoin, as discussed in Section 2. Thus, the implication is that though there are diversification benefits from investing in cryptocurrency and African stock markets, the diversification benefits decrease in crisis periods.

3.3 | Wavelet multiple correlation

To check the robustness of the transfer entropy results, we utilize WMC. Tweneboah et al. (2019) use WMC to explore the integration status of African markets using weekly data over a sample period stretching from 2011 to 2017. We adopt this method using daily data and a sample period that encompasses the COVID-19 period to determine the status of economic integration in the face of "black swan" events like the COVID-19 pandemic. We also explore bivariate correlation among the sample indices in a frequency–time domain. The results from the bivariate wavelet correlation are shown in Appendix A. The bivariate wavelet correlation coefficients are mostly negative and insignificant at any of the conventional levels of statistical significance. For bivariate relationships that are statistically significant, the entropy values are closer to zero than they are to 1, again showing evidence of weak bivariate linkages among African stock markets. The pattern exhibited in the bivariate relationships does change using multivariate WMC as shown in Figure 3.

Figure 3 again indicates the weak correlations among African stock exchanges. Though the coefficients increase with frequency, at wavelet scale 128, only about 70% of the variation can be explained by the market. The results depicted in Figure 3 are qualitatively comparable to Tweneboah et al. (2019). The WMCs shown in Figure 3 across the wavelet scales are low compared to coefficients reported in the Eurozone (between 0.96 and 1 from the lowest wavelet scale to the highest wavelet scale; Fernández-Macho, 2012) and Asia (between 0.8 and 0.95 from the lowest wavelet scale to the highest wavelet scale; Kumar Tiwari et al., 2013). This shows evidence of weak stock market integration in Africa compared to other regions. In summary, both the theoretic framework as well as the WMC approaches used in this study show weak support for stock market integration, as demonstrated by the mostly insignificant flow of information among the African stock exchanges. Several reasons can be postulated for these weak linkages, including the significantly different sizes and stages of development of African stock exchanges. Smaller stock exchanges like the Malawi Stock Exchange are highly illiquid and only recently started using automated trading systems. At the same time, some stock exchanges like the JSE are deep, sophisticated and embrace the latest technologies and products. Thus, the Malawi Stock Exchange would have to reach a certain level of development to be integrated with

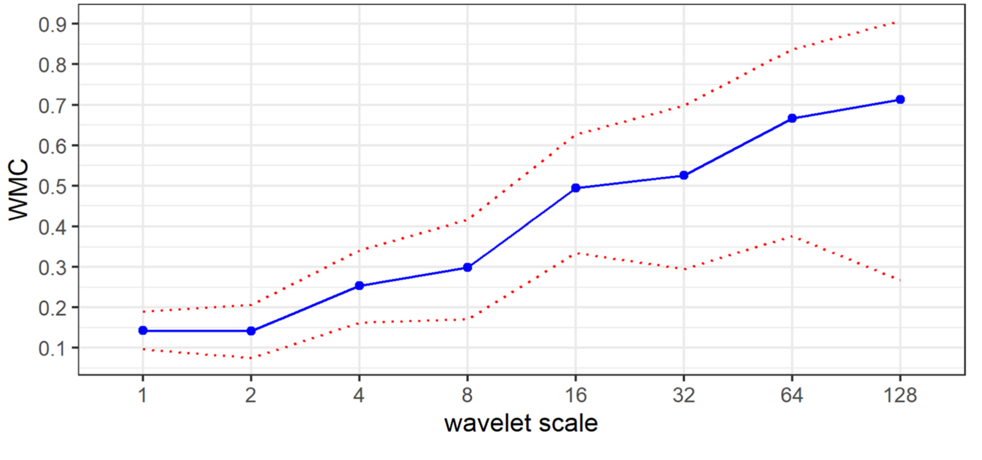

FIGURE 3 Wavelet multiple correlation plot of equity indices. The dashed lines correspond to the upper and lower bounds of the corresponding 95% confidence interval. [Color figure can be viewed at wileyonlinelibrary.com]

the JSE. Some reasons for segmentation among African stock exchanges can be traced to the colonial attachments of African countries. Stock market integration requires harmonization of rules as well as accounting and reporting standards. Yartey and Komla (2009) reason that harmonization of accounting and reporting standards may be an arduous task, as these tend to depend on countries' colonial histories. It is expected that the recently established AfCFTA will address some of these issues and use this as a stepping stone toward achieving the African Union Agenda 2063 and the establishment of a pan-African exchange.

4 | CONCLUSION

This study revisits the state of integration of stock exchanges in Africa using an information-theoretic framework based on transfer entropy. Though integration of stock markets in Africa has been widely explored in the literature, this study uses transfer entropy to quantify and determine the direction of flow of information among African stock exchanges. Transfer entropy has been reported as robust in the presence of stylized facts about financial variables, such as volatility clustering and long memory. It is a model-free method that does not assume a prior data generation process. We report evidence of weak integration of African stock exchanges, as shown by the mostly insignificant and low magnitudes of transfer entropy among the sample exchanges. With the growing importance of Bitcoin as an asset class in Africa, we also explore whether there are any diversification benefits from investing both in African equity and cryptocurrency. Our results show that the sample African stock markets are weakly integrated with Bitcoin and that there is a significant flow of information from Bitcoin to African stock markets since the onslaught of the COVID-19 pandemic for the three African countries that trade the most Bitcoin in terms of volume. These countries are Nigeria, South Africa and Kenya.

Our results have several policy implications. First, there are diversification benefits to investing in African stock markets, especially for the international investor. Second, Bitcoin provides an avenue for diversifying away from the risk of African equities, especially in stable periods. However, during crises, equities are affected by Bitcoin for those countries that trade the most Bitcoin. With the increasing usage and adoption of cryptocurrency in Africa, there is a strong chance that these countries will become more integrated with cryptocurrency and regulators should therefore be prepared when this happens, as this could destabilize financial systems. Third, the linear model of economic integration might be the best option for Africa, as it has worked in other regions. Though AfCFTA provides the best start for a linear model of economic integration, more effort should be put into ensuring increased intra-Africa trade. Future studies could examine whether the recently launched AfCFTA has the capacity to amplify the pace of the integration process of African stock markets.

AUTHOR CONTRIBUTIONS

Kingstone Nyakurukwa: Conceptualization; Formal analysis; Investigation; Methodology; Software; Writing—original draft. **Yudhvir Seetharam**: Investigation; Project administration; Resources; Supervision; Writing—review & editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data used for this study is available from Bloomberg Inc and investing. com. The data that support the findings of this study are not shared because the paper makes use proprietary data from the Bloomberg Terminal. Bitcoin data are publicly available at www.investing.com.

ORCID

Kingstone Nyakurukwa http://orcid.org/0000-0001-5854-4631
Yudhvir Seetharam https://orcid.org/0000-0003-4409-1015

ENDNOTES

[1] Cryptocurrency interest is measured as the number of crypto owners as a percentage of the population. Kenya, South Africa, and Nigeria occupy positions 4, 5, and 8 in the rankings, respectively (https://brokerchooser.com/education/crypto/crypto-countries).

[2] We use the date COVID-19 was declared a global pandemic by the World Health Organisation as the break date. For robustness, we also split the sample using the date the first COVID-19 case was reported in China and our results do not qualitatively change.

REFERENCES

Agyei-Ampomah, S. (2011). Stock market integration in Africa. *Managerial Finance*, *37*(3), 242–256. https://doi.org/10.1108/03074351111113306

Alagidede, P. (2009). Are African stock markets integrated with the rest of the world? *African Finance Journal*, *11*(1), 37–53. https://doi.org/10.10520/EJC33739

Aniche, E. T. (2020). African continental free trade area and African union agenda 2063: The roads to Addis Ababa and Kigali. *Journal of Contemporary African Studies*, 1–16. Advance online publication. https://doi.org/10.1080/02589001.2020.1775184

Atenya, M. K. (2019). The status quo of East African stock markets: integration and volatility. *African Journal of Business Management*, *13*(5), 176–187. https://doi.org/10.5897/AJBM2019.8742

de Best, R. (2021). *Bitcoin (BTC) trading volume in 44 countries worldwide in 2020*. Retrieved 11 December 2021, from https://www.statista.com/statistics/1195753/bitcoin-trading-selected-countries/

de Best, R. (2022). *Bitcoin trading volume, only using domestic currencies, on online exchanges in various countries worldwide in 2020*. https://www.statista.com/statistics/1195753/bitcoin-trading-selected-countries/

Boako, G., & Alagidede, P. (2017). Co-movement of Africa's equity markets: Regional and global analysis in the frequency–time domains. *Physica A: Statistical Mechanics and Its Applications*, *468*(C), 359–380.

Boamah, N. A. (2016). Regional and global market integration of African financial markets. *African Review of Economics and Finance*, *8*(2), 234–268. https://doi.org/10.10520/EJC198159

Bracker, K., Docking, D. S., & Koch, P. D. (1999). Economic determinants of evolution in international stock market integration. *Journal of Empirical Finance*, *6*(1), 1–27.

Bundoo, S. K. (2017). Stock market development and integration in SADC (Southern African development community). *Review of Development Finance*, *7*(1), 64–72. https://doi.org/10.1016/j.rdf.2017.01.005

Collins, D., & Biekpe, N. (2003). Contagion and interdependence in African stock markets. *South African Journal of Economics*, *71*(1), 181–194. https://doi.org/10.1111/j.1813-6982.2003.tb00077.x

Dimpfl, T., & Peter, F. J. (2013). Using transfer entropy to measure information flows between financial markets. *Studies in Nonlinear Dynamics and Econometrics*, *17*(1), 85–102. https://doi.org/10.1515/snde-2012-0044

Dorodnykh, E. (2014). Determinants of stock market integration. In E. Dorodnykh (Ed.), *Stock market integration: An international perspective* (pp. 50–83). Palgrave Macmillan. https://doi.org/10.1057/9781137381705_4

Emenike, K. O. (2021). Interdependence among West African stock markets: A dimension of regional financial integration. *African Development Review*, *33*(2), 288–299. https://doi.org/10.1111/1467-8268.12575

Fernández-Macho, J. (2012). Wavelet multiple correlation and cross-correlation: A multiscale analysis of Eurozone stock markets. *Physica A: Statistical Mechanics and Its Applications*, *391*(4), 1097–1104. https://doi.org/10.1016/j.physa.2011.11.002

Hailu, M. (2015). Regional economic integration in Africa: Challenges and prospects. *Mizan Law Review*, *8*(2), 299–332. https://doi.org/10.4314/mlr.v8i2.2

Karim, A. B., & Majid, M. S. A. (2010). Does trade matter for stock market integration? *Studies in Economics and Finance*, *27*(1), 47–66. https://doi.org/10.1108/10867371011022975

Kullback, S., & Leibler, R. A. (1951). On information and sufficiency. *The Annals of Mathematical Statistics*, *22*(1), 79–86. https://doi.org/10.1214/aoms/1177729694

Kumah, S. P., & Odei-Mensah, J. (2021). Are cryptocurrencies and African stock markets integrated? *The Quarterly Review of Economics and Finance*, *81*, 330–341. https://doi.org/10.1016/j.qref.2021.06.022

Kumar Tiwari, A., Billah Dar, A., Bhanja, N., & Shah, A. (2013). Stock market integration in asian countries: Evidence from wavelet multiple correlations. *Journal of Economic Integration*, *28*(3), 441–456.

Kunle, A., & Omoruyi, P. (2014). Empirics of demutualization of African stock exchanges: Lesson from Nigeria. *Journal of Finance and Investment Analysis*, *3*(2), 14.

Lehkonen, H. (2015). Stock market integration and the global financial crisis. *Review of Finance*, *19*(5), 2039–2094. https://doi.org/10.1093/rof/rfu039

Marschinski, R., & Kantz, H. (2002). Analysing the information flow between financial time series. *The European Physical Journal B—Condensed Matter and Complex Systems*, *30*(2), 275–281. https://doi.org/10.1140/epjb/e2002-00379-2

Mensah, J. O., & Alagidede, P. (2017). How are Africa's emerging stock markets related to advanced markets? Evidence from copulas. *Economic Modelling*, *60*, 1–10. https://doi.org/10.1016/j.econmod.2016.08.022

MSCI. (2022). MSCI announces the results of the 2022 annual market classification review. https://www.msci.com/our-solutions/indexes/market-classification

Nyakurukwa, K. (2021). Information flow between the Zimbabwe stock exchange and the Johannesburg Stock Exchange: A transfer entropy approach. *Organizations and Markets in Emerging Economies*, *12*(2), 353–376. https://doi.org/10.15388/omee.2021.12.60

Obadiaru, E. D., Obasaju, B. O., Omankhanlen, A. E., & Eyiolorunshe, D. T. (2020). Dynamic links between the Nigerian equity market and those of selected regional and developed countries. *Heliyon*, *6*(9), e04782. https://doi.org/10.1016/j.heliyon.2020.e04782

Obeng-Odoom, F. (2020). COVID-19, inequality, and social stratification in Africa. *African Review of Economics and Finance*, *12*(1), 3–37.

Schreiber, T. (2000). Measuring information transfer. *Physical Review Letters*, *85*(2), 461–464. https://doi.org/10.1103/PhysRevLett.85.461

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Solyman, E. (2017, November 20). *African stock market booms, but challenges remain*. https://dailynewsegypt.com/2017/11/20/african-stock-market-booms-challenges-remain/

Tweneboah, G., Junior, P. O., & Oseifuah, E. K. (2019). Integration of major African stock markets: Evidence from multi-scale wavelets correlation. *Academy of Accounting and Financial Studies Journal*, *23*(6), 1–15.

Yartey, C. A., & Komla, C. (2009). *Stock market development in Sub-Saharan Africa: Critical issues and challenges* (IMF working paper WP/07/209), pp. 1–35.

Yepes-Rios, B., Gonzalez-Tapia, K., & Gonzalez-Perez, M. A. (2015). The integration of stock exchanges: The case of the Latin American integrated market (MILA) and its impact on ownership and internationalization status in Colombian brokerage firms. *Journal of Economics, Finance and Administrative Science*, *20*(39), 84–93. https://doi.org/10.1016/j.jefas.2015.08.001

How to cite this article: Nyakurukwa, K., Seetharam, Y. (2023). Stock market integration in Africa: Further evidence from an information-theoretic framework. *International Finance*, 26, 2–18. https://doi.org/10.1111/infi.12419

APPENDIX A: BIVARIATE WAVELET CORRELATION COEFFICIENTS

		Wavelet scale								
		1	2	4	8	16	32	64	128	256
Bivariate wavelet correlation permutations	MXZA|MXEG	0.074*	0.041	0.196	0.232	0.396	0.381	0.368*	0.368*	0.389*
	MXZA|MXKE	0.052*	−0.006	−0.037	0.114	0.268*	0.325*	0.363	0.411	0.697
	MXZA|MXMA	0.086*	0.014	0.100*	0.080	0.147	0.333*	0.362	0.358	0.037
	MXZA|MXNI	0.017	0.038	0.016	0.127	30.244*	0.368	0.362*	0.488	0.537
	MXZA|MXTN	−0.000	0.004	0.083	0.127	0.009	0.064	0.199	0.001	0.153
	MXZA|MXBW	0.016	0.006	−0.034	0.001	0.016	−0.016	−0.306	−0.230	0.296
	MXEG|MXKE	0.006	0.044	0.037	0.148*	0.276*	0.329*	0.387	0.291	0.291
	MXEG|MXMA	0.085*	0.093*	0.158*	0.099	0.254*	0.327*	0.548*	0.591*	0.499
	MXEG|MXNI	0.030	0.055	0.054	0.159*	0.255*	0.318*	0.373	0.105	0.245
	MXEG|MXTN	0.012	0.017	0.009	0.059	0.065	0.249	0.239	0.083	0.1
	MXEG|MXBW	−0.020	−0.012	−0.067	−0.033	0.037	−0.043	−0.124	−0.241	−0.126
	MXKE|MXMA	0.076*	0.061	0.055	0.026	0.019	0.241	0.302	0.321	−0.052
	MXKE|MXNI	0.073*	0.104*	0.149*	0.135*	0.173	0.300*	0.545*	0.527	0.697
	MXKE|MXTN	0.044	−0.009	0.007	−0.039	0.037	0.132	0.138	0.058	0.189
	MXKE|MXBW	0.049*	−0.030	−0.016	−0.058	0.003	0.143	0.0129	0.108	0.254
	MXMA|MXNI	0.033	0.053	0.076	0.078	0.160	0.291	0.384	0.149	0.064
	MXMA|MXTN	0.025	−0.007	0.101	0.090	0.140	0.233	0.058	−0.210	−0.063
	MXMA|MXBW	0.020*	−0.021	−0.033	−0.044	0.084	0.182	−0.142	−0.301	−0.066
	MXNI|MXTN	0.029	0.042	0.059	0.017	−0.025	0.050	−0.135	−0.291	0.143
	MXNI|MXBW	−0.022	−0.042	−0.010	−0.031	0.051	0.096	0.048	0.082	0.500
	MXTN|MXBW	0.027	−0.035	−0.043	−0.033	−0.106	−0.135	−0.091	0.051	−0.123

*Statistical significance at the 5% level.