On the connection between clean energy stocks and African stock markets: does uncertainty due to infectious diseases matter?

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Abstract

Purpose – As financial markets for environmentally friendly investment grow in both scope and size, analyzing the relationship between green financial markets and African stocks becomes an important issue. Therefore, this paper examines the role of infectious disease-based uncertainty on the dynamic spillovers between African stock markets and clean energy stocks.

Design/methodology/approach – The authors employ the dynamic spillover in time and frequency domains and the nonparametric causality-in-quantiles approach over the period of November 30, 2010, to August 18, 2021.

Findings – These findings are discernible in this study's analysis. First, the authors find evidence of strong connectedness between the African stock markets and the clean energy market, and long-lived but weak in the short and medium investment horizons. Second, the BDS test shows that nonlinearity is crucial when examining the role of infectious disease-based equity market volatility in affecting the interactions between clean energy stocks and African stock markets. Third, the causal analysis provides evidence in support of a nonlinear causal relationship between uncertainties due to infectious diseases and the connection between both markets, mostly at lower and median quantiles.

Originality/value – Considering the global and recent use of clean energy equities and the stock markets for hedging and speculative purposes, one may argue that rising uncertainties may significantly influence risk transmissions across these markets. This study, therefore, is the first to examine the role of pandemic uncertainty on the connection between clean stocks and the African stock markets.

Keywords Infectious diseases, Spillovers, African markets, Green stocks, Nonparametric causality

Paper type Research paper

1. Introduction

The integration of financial markets has continued to generate critical discussion in the international finance literature due to the underlying implications on investment decisions. This issue has become interesting since including climate-friendly green equities into the global asset classes. One of the significant concerns of nations over the last decade is climate change; these nations have continued to produce remedying actions to ensure progression toward a climate-friendly economy. The investment in the clean energy sector across the globe was U.S. $279.8bn in 2017, and this has led to a 10% increase in the capacity of renewable power generation (equivalent to 157 gigawatts) more than the previous year and

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significantly higher than the proportion of power generated by conventional fossil fuels (New Energy Finance (NEF), 2018). In recent years, the contribution of clean energy shares in the stock market development has been substantial. In 2017, there was a 28% increase in clean energy share prices as quoted on the Wilder Hill New Energy Global Innovation Index, more significant than the corresponding year for S&P 500 share prices. In addition, the demand for clean energy has significantly increased by 36% in six years between 2015 and 2021, and by 2040, the sector is projected to have secured two-thirds of the world's investments in energy (Uddin *et al.*, 2019). This information, therefore, suggests plethoric investment opportunities in clean energy firms. Hence, understanding the dynamics of clean energy stock return is of great relevance. As much of the clean energy equity market's interactions with currency and commodity markets and the advanced stock markets have been examined (see *inter alia*, Sadorsky, 2012; Kumar *et al.*, 2012; Managi and Okimoto, 2013; Bohl *et al.*, 2013; Inchauspe *et al.*, 2015; Bondia *et al.*, 2016; Trabelsi, 2018; Bouri *et al.*, 2019; Pham, 2021; Pandey and Kumari, 2021), a similar investigation for the connection with the African stock markets has received less attention, granted that these markets are open to both local and foreign investors, despite their inefficiency, illiquidity, and weak connection relative to advanced stock markets (Mensah and Alagidede, 2017).

Based on the above insights and considering the global and recent use of clean energy equities and the stock markets for hedging and speculative purposes, one may also argue that rising uncertainties may significantly influence risk transmissions across these markets. Uncertainty shocks affect economic agents' decisions regarding employment, consumption, savings, and investment, which sets back macroeconomic activity and further depresses private investments. Specifically, uncertainties induced by infectious diseases (such as SARS, Ebola, and not forgetting COVID-19 outbreak) could have greater catastrophic effects, such as freezing global economic activities, a fall in aggregate demand, a surge in unemployment rates, a plunge in financial markets, leading to transnational financial chaos and distortion in asset allocations and risk management models (Bouri *et al.*, 2020). Consequently, this has renewed interest as many recent studies concentrate on infectious diseases' social, economic, and market effects (Baker *et al.*, 2020; Bouri *et al.*, 2020; Fasanya *et al.*, 2021a; Alon and Bretas, 2021; Akhtaruzzaman *et al.*, 2021b; Cicchiello *et al.*, 2022; Liu *et al.*, 2022; Harjoto and Rossi, 2023).

Motivated by the above, we analyze the volatility co-movements between renewable energy stocks and the African stock markets using both time and frequency domain connectedness approaches. We employ both the time-varying spillover technique, which is robust to several setbacks posed by other measures of connectedness, such as the degree of responsiveness to outlier caused by a Kalman filter generating process, results in susceptibility to a random selection of the rolling window size as well as losing the number of expected observations arising from the rolling window approach (see, Bouri *et al.*, 2020) and the Barunik and Krehlik [B.K. thereafter] (2018) frequency connectedness framework to analyze the spillovers between clean energy stocks and African stock markets across different investment frequencies. This technique analyses the connection between variables which follows a generalized forecast error variance decomposition framework that can be disintegrated into different periods (e.g. the short, medium, and long term) by applying spectral representations to the forecast error variance decomposition. This process permits the determination of cross spillovers among the variables of interest over separate and distinct frequency horizons, distinguishing the frequency bands or periods that offer the highest contribution to the connectedness framework among the variables.

Furthermore, unlike most studies in the literature which relate infectious diseases, clean energy equities, and other asset classes in separate settings, this study examines how infectious diseases affect the connections among distinct asset types, in our case, clean energy stocks and

African stock markets. Knowledge of the size and direction of net spillovers would be helpful for economic agents, environmentally conscious investors, and policymakers for enhancing portfolio decisions and the formulations of policy to restore and safeguard financial stability in the wake of catastrophic events, such as the Ebola and COVID-19 outbreaks (Bouri *et al.*, 2020). In this process, we assess how infectious diseases induced uncertainty affects the interactions between the clean energy stocks and African markets. To achieve this, we consider the non-linear causality-in-quantiles approach of Balcilar *et al.* (2016). This technique can figure out spontaneous causality in both returns and volatility at each point of a particular conditional distribution and provides a system for determining the existence of causality of variable distribution across different quantiles (Rehman and Apergis, 2018). The flexibility of the nonparametric causality approach also involves the ability to test the non-linear causality of different quantiles of the nth order of variable returns over the distribution period. Another interesting feature of this approach is its robustness to functional misspecification errors. It can observe overall dependence between financial time series, especially when there are obvious signs of structural breaks (Balcilar *et al.*, 2016). In addition, to justify the non-linearity in the series, the BDS test of Brock *et al.* (1996) is conducted on residuals of the directional connectedness equation in the VAR(1) model involving infectious diseases alternately. The results validate the nonparametric causality technique (as emphasized in Balcilar *et al.*, 2016; Fasanya *et al.*, 2021a, b; Periola-Fatunsi *et al.*, 2021).

The reason for investigating the relationship between clean energy stocks and African stock markets is multifaceted. The rising global interest in clean energy has led to a surge in investment in this sector. Examining the effects of this investment trend on African stock markets is imperative. Additionally, African nations are among the most vulnerable to the impact of climate change, making it essential to explore ways to leverage the clean energy sector's growth for sustainable development. Regarding the influence of infectious diseases on this relationship, uncertainty arising from infectious diseases can have several consequences. Outbreaks of infectious diseases can cause market volatility that impacts clean energy and African stock markets. For instance, the COVID-19 pandemic led to a global economic slowdown, which led to a sharp decline in oil prices and adversely affected the clean energy sector. Similarly, the pandemic also affected African stock markets, with several experiencing significant declines in value.

Furthermore, infectious diseases can affect the development and deployment of clean energy technologies, particularly in Africa, where several countries lack the necessary infrastructure and resources to combat outbreaks. For example, the Ebola outbreak in West Africa in 2014–2015 led to a decline in investment in the region, adversely affecting the clean energy sector's growth. Hence, understanding the relationship between clean energy stocks and African stock markets and the influence of infectious diseases is crucial for policymakers, investors and other stakeholders to make well-informed decisions regarding investment, development and sustainable growth.

Our paper contributes to the extant works in the following ways. First, we use time and frequency spillover connectedness frameworks to examine the spillovers between clean energy stocks and African stock markets. Second, we capture how infectious diseases affect the connections between clean energy and African stocks. This shows the dearth of research compared to studies involving infectious diseases and other asset classes in different settings (see, Balcilar *et al.*, 2016; Akhtaruzzaman *et al.*, 2021a,b; Pham, 2021; Harjoto and Rossi, 2023). However, this contribution is supported by applying the non-linear causality-in-quantile technique, which serves as our next contribution. Considering a non-linear causality framework, our study can analyze mean and variance causalities with higher-order dependencies. This becomes highly relevant when there is no sign of causality-in-mean, while, at the same time, higher-order interdependencies may turn out to be significant (Balcilar *et al.*, 2016). Lastly, this study analyzes daily intraday datasets divided into two regimes, COVID-19 and the full samples, which would help design optimal portfolios and hedging strategies during global uncertainties.

The rest of the paper is structured as follows. Section 2 reviews relevant literature, while Section 3 describes the methodology employed in the empirical analysis. Section 4 presents the data and empirical results, and Section 5 concludes the study.

2. Literature review

Given the increasing interest in clean energy among academics to understand its characteristics, particularly regarding its risk, return, hedging possibilities and connectedness to other markets, there has been an increasing abundance of knowledge on the subject. For example, having observed a dearth in the literature on the risk and returns characteristics of clean Energy stocks in relation to other equity segments, Kuang (2021) assessed the risk-return nexus of clean energy stocks using different optimization techniques. The paper assessed how clean energy stocks compare to "dirty energy" stocks. The results derived from this paper showed that although clean energy outperformed "dirty energy" stocks, they underperformed the traditional equity market on a risk-adjusted basis. The analysis by Kuang (2021) also disaggregated the clean energy by sub-sector and observed that the sub-sectors differed where risk and return potential were concerned. However, unlike Kuang (2021), Shahzad *et al.* (2020) looked at another aspect on which little had been said in the literature by revisiting the Efficient Market Hypothesis (EMH) in relation to Clean Energy Markets. The hypothesis proposes different degrees of stock market efficiency as concerned with investors' ability to achieve arbitrage profits in light of the market's speed of adjustment to public information. Specifically, they focused on the possibility of multifractality in the Clean Energy Markets, where stock values fall into potentially predictable patterns over some periods. Evidence of the existence of multifractality would contradict the proposition that the weak form of EMH holds for Clean Energy Markets. To achieve this objective, Shahzad *et al.* (2020) used the asymmetric Multifractal Detrended Fluctuation Analysis technique (Asymmetric MF-DFA) on three indices indicating the performance of the USA, European, and Global Energy markets. Using the technique above, they found three markets had notable asymmetric multifractality, meaning that the weak form EMH does not hold for the Clean Energy Market. Moreover, using the Market deficiency measure (MDM), the US clean Energy Stock market was the most efficient among the three markets assessed.

Spurred by the gap in knowledge concerning how the COVID-19 pandemic affected the link between the clean energy and "dirty energy" markets, Umar *et al.* (2021) examined the second-moment connectedness between the two markets using the Diebold & Yilmaz and Barunik & Krehlik approaches to spillover analysis. While they could only uncover a weak volatility link between clean energy and fossil fuel markets, they also found that the spillovers among energy markets did not exist with any intensity in the short run. They found that the contagion phenomenon intensified in crisis periods such as COVID-19. This is similar to the findings of Akhtaruzzaman *et al.* (2021b) which examines how financial contagion occurs through financial and nonfinancial firms between China and G7 countries during the COVID–19 period. Unlike Umar *et al.* (2021), who used data on the S&P Global Clean Energy index, Qi *et al.* (2022) focused on the Chinese economy and explored the dynamic association between clean energy stock markets and energy commodities using the Barunik and Krehlik (2018) time-varying dynamic connectedness methodology. From static connectedness, they found that clean energy markets were the principal net contributors and receivers in the short run. In the long run, energy commodity markets were the net contributors. Furthermore, from the dynamic connectedness, they found that the overall result is that short-term spillovers dominated the long-run spillovers. However, during the COVID-19 period of their data, they observed a reversal where long-term spillovers dominated short-term spillovers. Of practical relevance, Qi *et al.* (2022) proposed, on account of this finding, that because the energy commodity markets were less affected by clean energy markets in the long run, they potentially presented a possible hedging opportunity. Using the Morgan Stanley Capital International daily stock indices data and the Carhart and the GARCH(1,1) models for an event study, Harjoto and Rossi (2023) observe that the markets recovered quicker from the COVID-19 pandemic announcement than during the 2008 global financial crisis.

While Qi *et al.* (2022) looked at the Chinese economy in isolation, Janda *et al.* (2022) examined the nature of the return and volatility spillovers between oil prices and technology companies in the USA and China as Clean Energy Markets in these countries. The three multivariate GARCH model specifications used in the paper (that is VAR(1)-CCC-GARCH(1), VAR(1)-DCC-GARCH(1), and VAR(1)-ADCC-GARCH(1)) showed that prior returns from U.S renewable energy companies influenced the current returns of their Chinese counterparts. From estimating the VAR(1)-DCC-GARCH(1) and VAR(1)-ADCC-GARCH(1), Janda *et al.* (2022) found that, among those time series included in their analysis, Invesco China Technology ETF (CQQQ), an exchange-traded fund which tracks just over hundred publicly listed Chinese Tech firms, was the most appropriate asset to hedge exposures to Chinese Clean Energy markets.

Following papers such as Bianchi *et al.* (2020) and Yahya *et al.* (2020) that non-ferrous metals may possess hedging possibilities for clean energy equity exposure, Chen *et al.* (2022) examined the spillover effects among non-ferrous metals asset prices and several sub-sector Clean energy stocks using the Diebold and Yilmaz (2012) as well as the Barunik and Krehlik (2018) spillover indices. Much like the analyses found in Umar *et al.* (2021) and Qi *et al.* (2022), this approach involved network analysis in assessing possible contagion and routes of spillovers. The analysis uncovered several interesting results, but two are particularly relevant to the present study. First, the direction of spillovers varies, and the intensity rises as crises surface. Second, because non-ferrous metals transmit and receive the least in the time and frequency domains at once, they may be used in portfolio hedging strategies to reduce Clean Energy Stock markets. This finding adds empirical evidence to the theory that, as non-ferrous metals are essential raw inputs for the clean energy industry, exposure thereof is expected to reduce overall risk exposure to clean energy stocks.

Unlike the preceding literature, other studies focused on infectious diseases in clean energy security markets, Tian *et al.* (2022) looked at the green bond market by focusing on the possible asymmetric effects that several factors, including infectious disease-induced uncertainty, may have on green bond prices in the USA, Chinese and European markets. Using the non-linear ARDL, they found that only the Chinese green bond market was significantly affected by infectious disease-induced uncertainty. This finding was consistent with previous studies by Yi *et al.* (2021), who found that the COVID-19 pandemic greatly affected the Chinese green bond market. Interestingly, there was evidence that the US green bond market was not affected to any significant degree (Tian *et al.*, 2022). They concluded that the US, Chinese, and European green bond markets showed heterogeneous responses to uncertainty. These findings were consistent with the study by Gupta *et al.* (2020), who found that disease-linked uncertainty did not affect the US treasury securities market much.

Moreover, Gupta *et al.* (2020) concluded that these securities acted as a haven in the advent of infectious diseases such as the COVID-19 pandemic. Akhtaruzzaman *et al.* (2021b) investigate how financial contagion occurs between China and the G7 countries via financial and nonfinancial firms during COVID-19. According to the empirical findings, listed firms in these countries, both financial and non-financial, experience a significant increase in conditional correlations between their stock returns. However, during the COVID-19 outbreak, the magnitude of the increase in these correlations is significantly higher for financial firms, indicating the importance of their role in financial contagion transmission.

Tian *et al.* (2022) proposed that the US, Chinese and European markets showed different responses to uncertainty because the USA and European markets were more mature and enjoyed higher participation from experienced institutional investors. This contrasts with the Chinese green bond market, which did not enjoy the same privilege.

Despite the significant work done to understand better the characteristics of clean energy as well as its association with other markets, to the best of our knowledge, few or no studies have yet examined how the dynamics of the clean energy market's association with African stock markets may be affected by emergent infectious diseases such as COVID-19. Therefore, the present study contributes to the literature by addressing this gap in the literature. Specifically, the study accomplishes this objective by applying the Time-varying volatility connectedness framework of Antonakakis *et al.* (2020) and the Frequency-domain volatility connectedness framework of Barunik and Krehlik (2018). Moreover, given the likelihood of non-linearity, we supplement our analysis by applying the causality in the quantile technique.

3. Methodology

The methodology is structured into two stages. The first stage describes the spillover approaches in the time and frequency domain. After examining the spillovers across time and frequency bands, the next phase is the linear and non-linear causality analysis of pandemic uncertainty on the directional spillovers between clean energy stocks and African stock markets.

3.1 Spillover frameworks

3.1.1 Time-varying connectedness framework. Following the framework of Antonakakis *et al.* (2020), we calculate the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) in analyzing the dynamic spillovers and the degree of connectedness.

$$\widetilde{\rho}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \alpha_{\mathrm{ij,t}}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \alpha_{\mathrm{ij,t}}^2} \tag{1}$$

with $\sum_{j=1}^{n} \widetilde{\rho}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{n} \widetilde{\rho}_{ij,t}(H) = m$

The representation in (1) shows the cumulative effect of the overall shocks as captured in the denominator, while the numerator characterizes the singular shock cumulative effect in variable *i*. After, the total spillover index is derived through the GFEVD.

$$C_t(H) = \frac{\sum_{i,j=1, i\neq j}^{m} \widetilde{\rho}_{ij,t}(H)}{\sum_{i,j=1}^{m} \widetilde{\rho}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1, i\neq j}^{m} \widetilde{\rho}_{ij,t}(H)}{m} * 100 \tag{2}$$

Equation (2) describes the process of the spillover analysis where the direction of the connection between the variables is unraveled. In analyzing this direction, we compute the total directional spillover to and from others such that the difference between them generates the net spillover index. The process of transmitting shocks from variable i to other variables j defines the total directional spillovers to others as presented in equation (3), while equation (4) shows how shocks i are received from other variables j - directional spillovers from others.

$$C_{i\to j,t}(H) = \frac{\sum_{i,j=1, i\neq j}^{m} \widetilde{\rho}_{ji,t}(H)}{\sum_{i,j=1}^{m} \widetilde{\rho}_{ji,t}(H)} * 100 \tag{3}$$

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{m}\widetilde{\rho}_{ij,t}(H)}{\sum_{i,j=1}^{m}\widetilde{\rho}_{ij,t}(H)} * 100 \tag{4}$$

The difference between equations (3) and (4) defines the net total directional spillovers as shown in equation (5). The sign of $C_{i,t}$ is used to explain the relevance of variable i on the computed network; if positive, variable i has more effect on the network than itself, and if negative, then the network has more influence on variable i.

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \tag{5}$$

To better understand the directional spillovers, we compute the net pairwise directional spillovers (as shown in equation 6) to explain the bidirectional connectedness between the variables. If $NPDC_{ij}(H) < 0$ ($NPDC_{ij}(H) > 0$), It means that variable i is dominated by (dominates) variable j.

$$NPDC_{ij}(H) = \left(\widetilde{\rho}_{jit}(H) - \widetilde{\rho}_{ijt}(H)\right) * 100 \tag{6}$$

3.1.2 Frequency-domain connectedness framework. In order to examine the connectedness across different frequency bands, we follow the approach of B.K. (2018) to assume a frequency response function $\Psi(e^{-iw}) = \sum_h e^{-iwh}\Psi_h$ derived from Ψ, which represents the coefficients of the Fourier transform, with $i = \sqrt{-1}$. Over the frequencies, $\omega = \in(-\pi, \pi)$, the generalized causation spectrum is specified as:

$$(f(\omega))_{j,k} \equiv \frac{\sigma_{kk}^{-1}\left|\left(\Psi\left(e^{-iw}\right)\Sigma\right)_{j,k}\right|^2}{\left(\Psi\left(e^{-iw}\right)\Sigma\Psi'\left(e^{+iw}\right)\right)_{j,j}} \tag{7}$$

where is $\Psi(e^{-iw})$ represents the Fourier transform of the impulse response Ψ. It is essential to document that the fraction of the spectrum of the $j-th$ variable at frequency ω as caused by shocks in the $k-th$ variable is represented by $(f(\omega))_{j,k}$, and it is defined as the within-frequency causation measure. In line with B.K. (2018), the GFEVD on certain frequency band d is given as:

$$(\theta_d)_{j,k} = \frac{1}{2\pi}\int^{d}\Gamma_j(\omega)(f(\omega))_{j,k}d\omega \tag{8}$$

where $\Gamma_j(\omega)$ *is* taken as the function for weighting. Considering the spectral representation of the GFEVD, the frequency-based connectedness on the frequency band d is defined thus:

$$C_d^F = 100\left(\frac{\sum_{j\neq k}\left(\widetilde{\theta}_d\right)_{j,k}}{\sum\left(\widetilde{\theta}_\infty\right)_{j,k}} - \frac{Tr\left\{\widetilde{\theta}_d\right\}}{\sum\left(\widetilde{\theta}_\infty\right)_{j,k}}\right) \tag{9}$$

The total connection index is then computed as follows:

$$C_d^W = 100\left(1 - \frac{Tr\left\{\widetilde{\theta}_d\right\}}{\sum\left(\widetilde{\theta}_d\right)_{j,k}}\right) \tag{10}$$

Just like the time-based connectedness of Diebold and Yılmaz (2014), we can also compute the directional connectedness either "to others" (equation 11), "from others" (equation 12), and the net spillovers (equation 13) across the frequencies chosen.

$$\left(C_d^F\right)_{j\rightarrow} = 100 \times \left(\sum_{j\neq k,k}\left(\widetilde{\theta}_d\right)_{j,k}\right)\frac{\sum\left(\widetilde{\theta}_d\right)_{j,k}}{\sum\left(\widetilde{\theta}_\infty\right)_{j,k}} \tag{11}$$

$$\left(C_d^F\right)_{j\leftarrow} = 100 \times \left(\sum_{j\neq k,k}\left(\widetilde{\theta}_d\right)_{k,j}\right)\frac{\sum\left(\widetilde{\theta}_d\right)_{k,j}}{\sum\left(\widetilde{\theta}_\infty\right)_{k,j}} \tag{12}$$

$$\left(C_d^F\right)_{j,net} = \left(C_d^F\right)_{j\rightarrow} - \left(C_d^F\right)_{j\leftarrow} \tag{13}$$

Intuitively, the sign of $(C_d^F)_{j,net}$ explains if it is a receiver or a transmitter of shocks. If positive, it gives shocks to the network, and negative if otherwise.

3.2 Non-linear causality-in-quantile technique

After the analysis of the spillover index, we present the non-linear causality methodology of Balcilar *et al.* (2016), which extends the frameworks of Nishiyama *et al.* (2011) and Jeong *et al.* (2012) through the process of a second-moment non-linear causality test. Following Jeong *et al.* (2012) paper, we take the variable y_t as the predictor - (EMV_ID), which does not cause the predictant, in this case, z_t (stock market spillovers) in the $\sigma - quantile$ with respect to the lag-vector of $\{z_{t-1}, \ldots, z_{t-q}, y_{t-1}, y_{t-m}\}$ if

$$X_\sigma(z_t|z_{t-1}, \ldots, z_{t-m}, y_{t-1}, \ldots, y_{t-m}) = X_\sigma(z_t|z_{t-1}, \ldots, z_{t-m}) \tag{14}$$

While y_t causes z_t in the σth quantile with respect to $\{z_{t-1}, \ldots, z_{t-m}, y_{t-1}, y_{t-m}\}$ if

$$X_\sigma(z_t|z_{t-1}, \ldots, z_{t-m}, y_{t-1}, y_{t-m}) \neq X_\sigma(z_t|z_{t-1}, \ldots, z_{t-m}) \tag{15}$$

In extending the framework of Jeong *et al.* (2012), Balcilar *et al.* (2016) developed a higher moment causality test through the non-linear granger causality framework of Nishiyama *et al.* (2011). To demonstrate the higher-order moment causality, they take

$$z_t = f(K_{t-1}) + \beta(Q_{t-1})\gamma_t, \tag{16}$$

where γ_t is the white noise process, and $f(\cdot)$ and $\beta(\cdot)$ equals the unknown functions that satisfy pertinent conditions for stationarity. Although, this specification allows not granger-type causality testing from Q_{t-1} *to* z_t, however, it could detect the "predictive power" from Q_{t-1} *to* z_t^2 when $\beta(\cdot)$ is a general non-linear function. Thus, equation (16) is re-formulated to account for the null and alternative hypothesis for causality in variance in equations (17) and (18), respectively.

$$H_0 = P\left\{F_{z_t^2|V_{t-1}}\{X_\sigma(z_t|V_{t-1})\} = \sigma\right\} = 1, \tag{17}$$

$$H_1 = P\left\{F_{z_t^2|V_{t-1}}\{X_\sigma(z_t|V_{t-1})\} = \sigma\right\} < 1, \tag{18}$$

We obtain the feasible test statistic for testing the null hypothesis in equation (17). With the inclusion of Jeong *et al.* (2012) approach, Balcilar *et al.* (2016) overcome the issue that causality in mean implies causality in variance. Specifically, they interpret the causality in higher-order moments through the use of the following model:

$$y_t = f(K_{t-1}, Q_{t-1}) + \beta_t, \tag{19}$$

Thus, the higher order quantile causality is;

$$H_0 = P\left\{F_{z_t^n|V_{t-1}}\{X_\sigma(z_t|V_{t-1})\} = \sigma\right\} = 1, for\, n = 1, 2, \ldots, n, \tag{20}$$

$$H_1 = P\left\{F_{y_t^n|W_{t-1}}\{X_\sigma(z_t|V_{t-1})\} = \sigma\right\} < 1, for\, n = 1, 2, \ldots, n. \tag{21}$$

In general, we test that x_t granger causes y_t in σth quantile up to the N-th moment through the use of equation (20) to construct the test statistic of the equation of the first moment (null hypothesis) for each *n,* and this is subsequently extended to the higher value of N. In the end, we test for the existence of causality-in-mean and variance successively.

4. Discussion of results

4.1 Data and preliminary analyses

This study analyzes the connectedness between the ten (10) African Stock markets (namely: Egypt, Kenya, Mauritius, Morocco, Namibia, Nigeria, South Africa, Tunisia, Zambia, and Zimbabwe) and the Clean Energy Stock market in the face of market risks arising from uncertainty due to infectious diseases. Therefore, we adopt daily data from November 30, 2010, to August 18, 2021, based on data availability and the need for the series to have the same start and end dates. The analyses are conducted using the full sample and the sample covering the COVID-19 pandemic period. Data on African and Clean Energy Stock markets are obtained from the Thomson Reuters DataStream.

The Infectious Disease Equity Market Volatility (EMV-ID), a proxy for uncertainties due to infectious diseases, was developed by Baker *et al.* (2020) and is available for download from http://www.policyuncertainty.com. It is expedient to note that the returns of the series (r_t) are computed as the first difference of the natural logarithm of the level series (Pt); this is expressed as; $r_t = (\Delta \log(p_t)) \times 100$, where ($r_t$) represents the calculated returns of African stock market indices and clean energy stocks under study. (P_t) represents their respective price levels.

As a common practice in the empirical literature, we present preliminary results indicating the statistical properties of the underlying series. The descriptive statistics, using the returns series of the underlying variables, are summarized in Table 1. First, we record marginal positive and negative average values across the board, likely attributable to the adverse effect of the COVID-19 pandemic. Furthermore, the standard deviation, which measures some level of volatility in time series, shows mild evidence of volatilities across the series considered, except for Zimbabwe and EMV_ID, which demonstrate high volatility attributes. At the same time, Tunisia and Morocco exhibit the lowest volatilities (0.912 and 0.919 respectively). Unsurprisingly, the Jarque-Bera test rejects the null hypothesis of normal distribution for all the series following the reports of the skewness and kurtosis statistics. While the skewness values are negative for all the returns series, their kurtosis estimates exceed the standard threshold. This suggests the presence of extreme fluctuations in these markets. This is common in financial time series (Fasanya *et al.*, 2021a).

Results from the brief descriptive analysis have the following implications. First, the non-normality of the series gives a relative indication of heavy right or left tail and excess kurtosis, which suggests the likely presence of non-linearity and/or structural shifts along the time paths of the series, implying that using linear or constant parameter models would bring about spurious results. This justifies the choice of a non-linear quantiles-based causality test. Second, heavy tails and high levels of volatility necessitate examining the relationship in both

Table 1.
Summary statistics

	Panel A: Summary statistics									Panel B: Unit root results	
	Mean	Median	Max	Min	S.D.	Skew	Kurt	Jarque Bera	Obs	ADF	PP
Clean Stocks	0.015	0.061	11.035	−12.498	1.460	−0.620	11.492	8580.930	2,796	−18.519c***	−47.280c***
Egypt	−0.018	0.000	10.459	−38.223	1.746	−4.661	93.433	96286.615	2,796	−47.242c***	−47.047c***
Kenya	0.032	0.041	4.786	−7.135	1.073	−0.586	7.593	2,617.102	2,796	−38.901c***	−38.647c***
Mauritius	−0.009	0.000	13.144	−15.299	1.095	−1.451	45.522	21162.900	2,796	−48.697c***	−48.755c***
Morocco	−0.010	0.008	5.031	−9.918	0.919	−0.622	12.229	10102.877	2,796	−48.168c***	−48.153c***
Namibia	0.010	0.038	14.996	−30.966	1.281	−4.612	134.228	20161.883	2,796	−58.972c***	−59.958c***
Nigeria	−0.026	0.000	8.479	−29.046	1.394	−3.643	76.494	63544.975	2,796	−34.840c***	−41.984c***
South Africa	−0.005	0.072	8.341	−12.346	1.777	−0.486	6.929	1908.219	2,796	−51.592c***	−51.834c***
Tunisia	−0.009	−0.016	5.394	−5.335	0.912	−0.129	6.599	1516.865	2,796	−48.976c***	−48.849c***
Zambia	−0.038	−0.029	9.408	−14.902	1.336	−0.361	15.478	18201.091	2,796	−51.147c***	−51.147c***
Zimbabwe	0.020	0.000	18.392	−274.491	6.125	−33.280	1459.896	247792.152	2,796	−49.349c***	−49.476c***
EMV_ID	2.999	0.000	68.370	0.000	7.691	3.655	19.031	36178.231	2,797	−4.032c***	−20.837c***

Note(s): The table is organized into two panels. Panel A presents descriptive statistics of the variables, while Panel B presents unit root test results. “c” is the model with constant and deterministic trend as exogenous lags are selected based on Schwarz info criteria. *** implies that the series is stationary at 1%
Source(s): Compiled by the authors

the conditional-mean and conditional variance (see Fasanya *et al.*, 2021c). Unit root test results also reveal that all series are stationary at the 1% significance level. From the analysis of the graphical illustrations in Figure 1, there is strong evidence indicating market reactions regarding stock returns to uncertainty due to infectious diseases, especially since the late period of the year 2019, which was the inception of the COVID-19 outbreak.

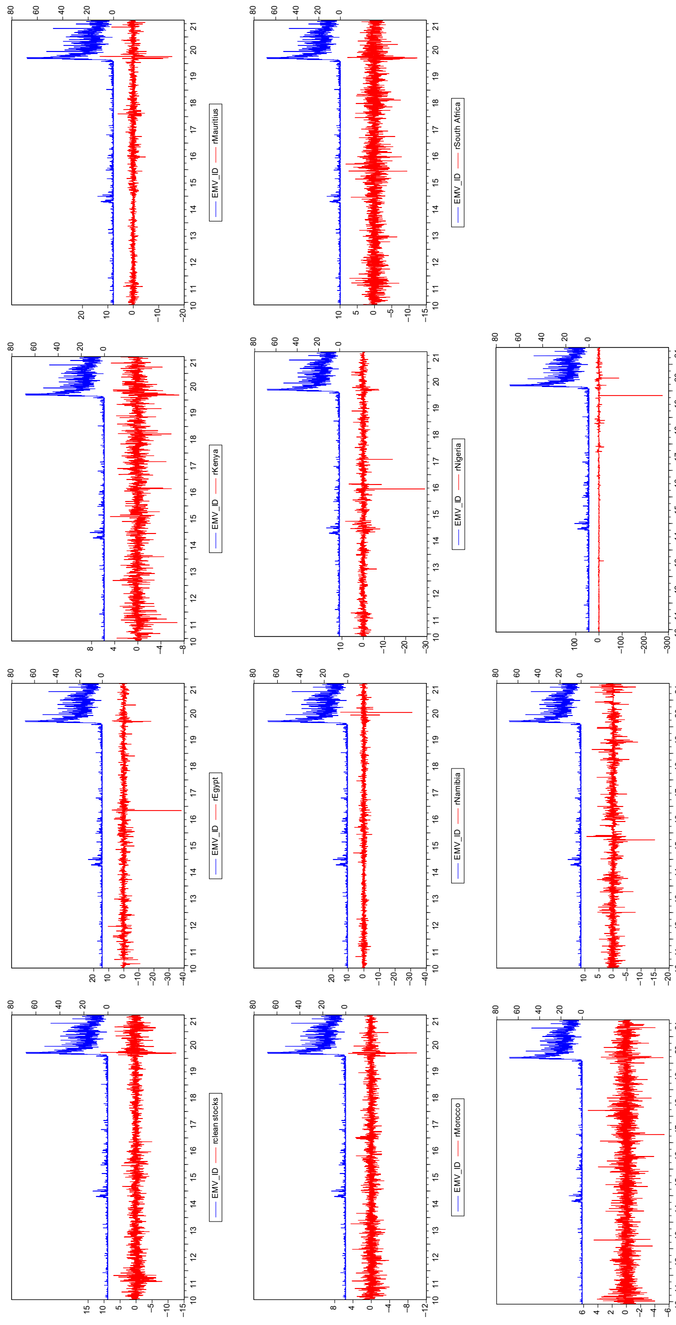
4.2 Spillover results

Intending to examine the volatility interactions between both markets, we present two (2) strands of results; the Time-Varying Vector Autoregression (TVP-VAR) for the time domain and Barunik and Krehlik (2018) for the frequency domain (frequencies considered are 1–4 days, 4–8 days, 8–15 days and more than 15 days) connectedness measures. First, we examine the dynamic volatility spillover among the markets using the TVP-VAR for the time domain. Table 2 presents the averaged connectedness measures following the TVP-VAR approach. Results suggest moderately increased connectedness between the markets as the TCI value of 36.3% indicates that 36.3% of the forecast error variance in one asset can be attributed to the innovations in all others. Second, we obtain the net directional spillover by subtracting the total contributions received by an asset FROM others from the total contributions it gives TO others. Positive (negative) values indicate that the asset is a net shock giver (receiver). Our results reveal a moderate spillover effect across the markets, with all significantly giving and receiving.

On average, Zimbabwe is the only net giver of shocks with 169%. In contrast, Nigeria (−23.3%), Kenya (−22%), Zambia (−21.8), and Tunisia (−19.4%) are the highest net shock receivers, implying that they receive more than they transmit. The net spillover results in Table 3 are also consistent with the graphical illustration in Figure 1 and the net spillover graphs in Figure 2. These results strongly align with expectations, corroborating the descriptive results in Table 1, showing that Zimbabwe exhibits positive returns. However, in terms of diversification options, results show that Egypt and Namibia (8.7 and 8.8%, respectively) are best effective portfolio diversification options for investors in the African Stock markets as they show the weakest vulnerability to idiosyncratic shocks from other African stock markets while Zimbabwe is the highest contributor. Therefore, investors in African stocks may use Egypt and Namibia to obtain their targeted returns through minimal risk exposure.

Regarding the contribution to others, we can see that gross directional volatility spillovers to others from each of the eleven markets span from 174.5% Zimbabwe to 9.5% Zambia. Also, evidence suggests a bi-directional relationship between Namibia and South Africa. Figure 3 also indicates increased connectedness within the African stock market and clean energy market since the COVID-19 inception in late 2019. The explanation for Zimbabwe's dominance can be traced to the period after the dollarization of Zimbabwe's economy following a period of hyperinflation. The economy became dollar driven, and since most commodities exports are valued in dollars, there is substantial cause for volatility co-movements.

Table 3 also presents the results of Barunik and Krehlik's (2018) net spillover indices for each market. The net spillovers in the positive domain represent the position when a country's stock market is a spillover contributor. In contrast, the negative domain represents a country's stock market as a spillover receiver. The empirical results demonstrate that clean energy stocks, Mauritius, Morocco, South Africa, and Zimbabwe are essentially net contributors of volatility across the four (4) frequencies considered, except for Nigeria, which becomes a net contributor in both the medium and long run and Kenya in long investment horizon alone. The net receivers of volatility spillovers across the four (4) frequency bands are Egypt, Kenya, Namibia, Nigeria, Tunisia, and Zambia. However, Nigeria and Kenya translate



Note(s): The figure reports combined graphs of Infectious Disease Equity Market Volatility (EMV-ID) and stock returns across countries

Source(s): Compiled by the authors

Figure 1.
Graphs showing the relationship between the EMV_ID and the return series of each African stock market

Table 2. Dynamic connectedness results (using TVP-VAR)

	Clean stocks	Egypt	Kenya	Mauritius	Morocco	Namibia	Nigeria	South Africa	Tunisia	Zambia	Zimbabwe	From
Clean Stocks	54.1	3	1.5	4	3.9	1.7	0.7	8.3	2.2	1.9	18.7	45.9
Egypt	2.3	66.8	1.1	1.8	1.7	1.5	1.3	3.8	1.9	1.4	16.4	33.2
Kenya	1.6	3.8	64.7	1.5	1.6	1.5	1.6	2.2	2.8	1.1	17.4	35.3
Mauritius	4.2	1.5	1.7	56.7	2.5	2.5	0.7	4.5	1.7	0.6	23.4	43.3
Morocco	4	1.4	1.3	2.4	62.1	1.2	1.2	3.9	1.7	2.2	18.7	37.9
Namibia	1.7	1.3	1.1	2.7	1.3	61.5	2.2	14.2	1	0.4	12.7	38.5
Nigeria	0.9	5.8	1.4	2	1.1	2.7	65	1.7	1.7	0.6	17.1	35
South Africa	10.2	2.8	1.6	5	4.4	12.6	0.9	42.7	1.4	0.5	17.9	57.3
Tunisia	2.1	1.6	1.6	2.5	2.5	4.5	1.7	1.8	64.2	0.5	17	35.8
Zambia	1.2	2.3	1.2	3.6	2.1	1.1	1.1	1.8	1.5	68.7	15.2	31.3
Zimbabwe	0.7	0.9	0.6	0.4	0.4	0.3	0.4	1.2	0.4	0.2	94.5	5.5
Contribution TO others	28.9	24.5	13.3	26	21.4	29.7	11.8	43.3	16.3	9.5	174.5	399
NET directional connectedness	−17	−8.7	−22	−17.3	−16.5	−8.8	−23.3	−14.1	−19.4	−21.8	169	TCI = 36.3

Note(s): Above table reports dynamic connectedness result between clean energy stocks and ten African markets. TCI represents total connectedness index
Source(s): Compiled by the authors

Table 3. B.K. (2018) Net pairwise spillover results

	Clean stocks	Egypt	Kenya	Mauritius	Morocco	Namibia	Nigeria	South Africa	Tunisia	Zambia	Zimbabwe	FROM_ABS	FROM_WTH
Freq1 The spillover table for bands 3.14 to 0.79 roughly corresponds to 1 day to 4 days													
Clean Stocks	0.9	0.01	0.03	0	0.14	0	0	0.27	0.01	0	0	0.04	0.35
Egypt	0.05	5.79	0	0.01	0.12	0	0	0.03	0	0	0	0.02	0.16
Kenya	0.5	0.01	11.43	0.31	0.28	0	0.01	0.23	0.02	0	0.04	0.13	1.03
Mauritius	0	0.01	0.03	2.08	0	0	0	0	0	0	0	0	0.04
Morocco	0.17	0.03	0.02	0	1.08	0	0	0.16	0.02	0	0	0.04	0.29
Namibia	0.01	0	0	0	0	51.02	0	0.14	0	0	0	0.01	0.11
Nigeria	0	0	0.03	0	0	0	21.15	0.04	0	0	0	0.01	0.06
South Africa	0.15	0	0.01	0	0.07	0	0	0.75	0	0	0	0.02	0.17
Tunisia	0.1	0	0.01	0.01	0.08	0	0	0.01	7.03	0	0	0.02	0.16
Zambia	0	0	0	0	0	0	0	0	0	9.48	0	0	0.01
Zimbabwe	0	0	0.02	0	0	0	0	0	0	0	23.09	0	0.02
To_Abs	0.09	0.01	0.01	0.03	0.06	0	0	0.08	0.01	0	0	0.3	
To_Wth	0.71	0.05	0.11	0.25	0.5	0	0.02	0.65	0.05	0	0.03		2.39
Net	0.0461	−0.0141	−0.1142	0.0267	0.0265	−0.0138	−0.0048	0.0592	−0.0131	−0.0007	0.0022		TCI = 0.2976
Freq2 The spillover table for bands 0.79 to 0.39 roughly corresponds to 4 days to 8 days													
Clean Stocks	0.91	0.01	0.09	0	0.16	0	0	0.27	0.02	0	0	0.05	0.59
Egypt	0.05	5.65	0.02	0.02	0.12	0	0	0.03	0	0	0	0.02	0.25
Kenya	0.46	0.01	10.21	0.28	0.24	0	0.02	0.22	0.02	0	0.07	0.12	1.38
Mauritius	0.02	0.01	0.05	2	0.01	0	0	0.01	0.01	0	0	0.01	0.11
Morocco	0.18	0.03	0.12	0.01	1.11	0	0	0.16	0.02	0	0	0.05	0.55
Namibia	0	0	0	0	0	20.08	0	0.06	0	0	0	0.01	0.07
Nigeria	0	0	0.02	0	0	0	17.06	0.03	0.01	0	0	0.01	0.07
South Africa	0.16	0.01	0.02	0	0.08	0	0.01	0.75	0	0	0	0.03	0.29
Tunisia	0.1	0.01	0.05	0.01	0.11	0	0.01	0.02	6.72	0	0	0.03	0.32
Zambia	0	0	0	0	0	0	0	0	0	9.04	0	0	0.02
Zimbabwe	0	0	0.02	0	0	0	0	0	0	0	18.22	0	0.03
TO_ABS	0.09	0.01	0.04	0.03	0.07	0	0	0.07	0.01	0	0.01	0.32	
TO_WTH	1.02	0.08	0.42	0.34	0.76	0.01	0.05	0.84	0.09	0.01	0.07		3.69
Net	0.0370	−0.0148	−0.0840	0.0201	0.0177	−0.0054	−0.0020	0.0478	−0.0194	−0.0008	0.0038		TCI = 0.3193

(*continued*)

	Clean stocks	Egypt	Kenya	Mauritius	Morocco	Namibia	Nigeria	South Africa	Tunisia	Zambia	Zimbabwe	FROM_ABS	FROM_WTH
Freq3 The Spillover Table For Band 0.39 To 0.21 Roughly Corresponds To 8 Days To 15 Days													
Clean Stocks	1.63	0.04	0.36	0.01	0.35	0	0.02	0.5	0.04	0	0	0.12	1.16
Egypt	0.09	9.26	0.07	0.03	0.22	0	0	0.05	0.01	0	0	0.04	0.41
Kenya	0.67	0.01	13.52	0.38	0.29	0	0.05	0.33	0.02	0	0.14	0.17	1.67
Mauritius	0.08	0.01	0.15	3.17	0.06	0	0	0.08	0.02	0	0	0.04	0.36
Morocco	0.35	0.07	0.57	0.04	2.04	0	0.01	0.29	0.04	0	0	0.12	1.21
Namibia	0	0	0	0	0	12.48	0	0.04	0.01	0	0	0	0.05
Nigeria	0.01	0	0.02	0.01	0	0	19.08	0.03	0.03	0	0	0.01	0.09
South Africa	0.31	0.03	0.1	0	0.17	0	0.04	1.33	0.02	0	0	0.06	0.58
Tunisia	0.17	0.02	0.24	0.01	0.32	0	0.03	0.04	10.43	0	0	0.08	0.73
Zambia	0	0	0.01	0	0	0	0	0	0.01	13.93	0	0	0.03
Zimbabwe	0	0	0.05	0	0	0	0	0	0	0	19.66	0.01	0.05
TO_ABS	0.15	0.02	0.14	0.04	0.13	0	0.01	0.12	0.02	0	0.01	0.66	
TO_WTH	1.48	0.15	1.36	0.43	1.24	0.01	0.13	1.2	0.17	0.02	0.14		6.34
Net	0.0334	−0.0271	−0.0312	0.0075	0.0035	−0.0035	0.0039	0.0639	−0.0575	−0.0018	0.0090		TCI = 0.6559
Freq4 The spillover table for bands 0.21 to 0.00 roughly corresponds to more than 15 days													
Clean Stocks	40.13	1.27	27.71	1.33	17.66	0.01	0.44	5.04	0.46	0	0.17	4.92	7.17
Egypt	2.8	67.81	3.11	0.67	3.11	0	0.03	0.82	0.02	0	0.02	0.96	1.4
Kenya	8.96	0.06	44.62	1.18	1.45	0	0.41	2.81	0.03	0	0.69	1.42	2.07
Mauritius	19.18	1.04	25.69	22.66	16.04	0.01	0.48	5.78	1.07	0.05	0.18	6.32	9.22
Morocco	15.03	0.91	31.26	3.3	39.21	0.02	0.3	2.75	0.47	0.02	0.19	4.93	7.2
Namibia	0.08	0	0.01	0	0.01	15.92	0	0.1	0.02	0.01	0	0.02	0.03
Nigeria	0.48	0.01	0.47	0.06	0.2	0.01	40.64	0.26	0.28	0.04	0	0.16	0.24
South Africa	25.04	3.02	23.44	0.95	19.26	0.02	1.42	21.72	0.89	0.01	0.22	6.75	9.85
Tunisia	2.84	0.27	9.53	0.35	10.27	0.01	0.38	0.5	50.23	0.07	0.04	2.2	3.22
Zambia	0.03	0.02	0.06	0.05	0.02	0.01	0	0.14	0.13	67	0.01	0.04	0.06
Zimbabwe	0	0	0.19	0.01	0	0	0.01	0.02	0.02	0.02	38.65	0.02	0.04
TO_ABS	6.77	0.6	11.04	0.72	6.18	0.01	0.32	1.66	0.31	0.02	0.14	27.76	
TO_WTH	9.87	0.88	16.11	1.05	9.02	0.01	0.46	2.42	0.45	0.03	0.2		40.5
Net	1.8502	−0.3605	9.6240	−5.6012	1.2513	−0.0119	0.1507	−5.0964	−1.8963	−0.0236	0.1137		TCI = 27.7574

Note(s): Above table reports dynamic connectedness results between clean energy stocks and ten African markets at different frequencies. TCI represents the total connectedness index

Source(s): Compiled by the authors

Table 3.

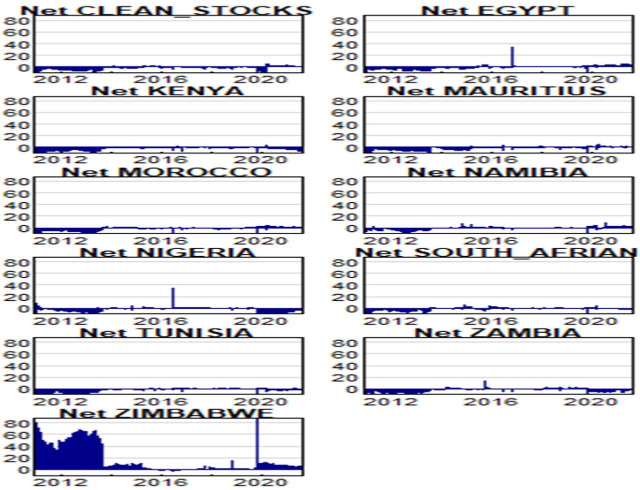


Figure 2.
Net total directional connectedness

Note(s): The figure reports graphs of net total directional connectedness results between 2010 and 2021
Source(s): Compiled by the authors

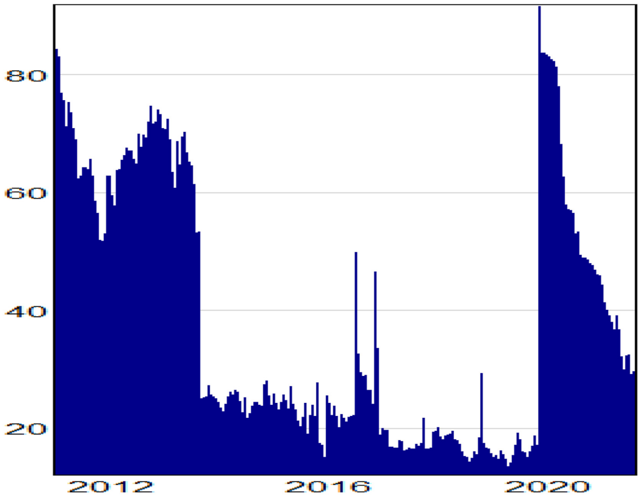


Figure 3.
Dynamic total connectedness

Note(s): The figure reports a graph of dynamic total connectedness results between African stock markets and the clean energy market from 2010 to 2021
Source(s): Compiled by the authors

to net contributors in Freq. 3 and Freq. 4, respectively. In comparison, Mauritius and South Africa become net receivers in Freq. 4, perhaps due to the effect of the global pandemic.

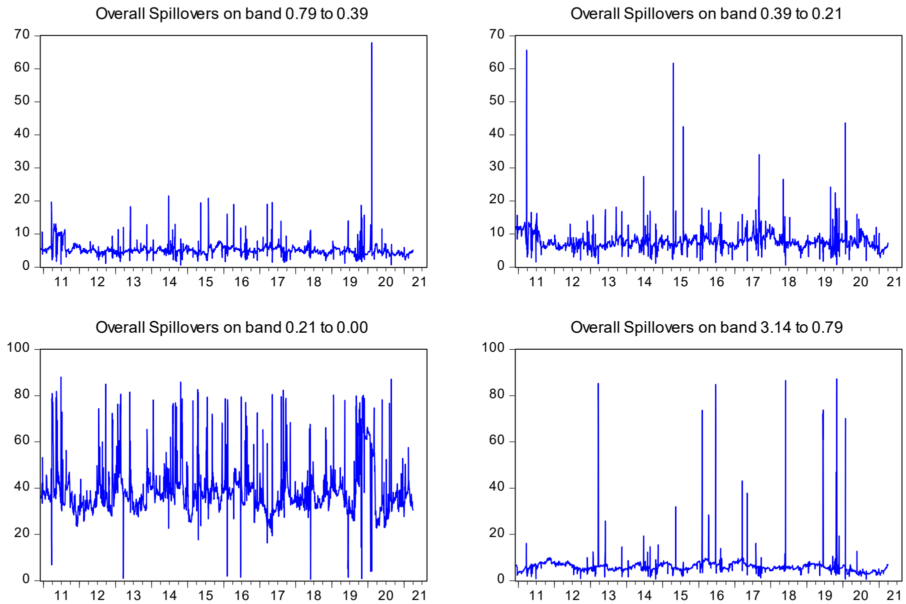
Kenya is the most significant contributor of volatility, with its major contribution coming in the long run. At the same time, Mauritius is the largest receiver of volatility spillovers across different investment horizons. The empirical results further explain that in the total connectedness, the maximum contribution (27.76%) is observed at the highest frequency (i.e. above 15 days), followed by the second highest frequency (0.66%) that corresponds to 8–15 days and the lowest contribution is made by the short-term frequency (0.3%) that corresponds to 1–4 days.

The frequency domain results (see Figure 4) show that a great degree of fluctuation is observed during the medium-term and long-term periods from 8–15 days ranging from about 1% to 90%, while lower fluctuations are seen in 4–8 days period which is about 0.5–65%. Both time and frequency measures quantitatively deliver similar results. The explanation for this structural break is that before late 2019, international commodity prices have risen substantially due to strong global economic growth and increased demand in emerging markets, particularly from China. Commodity exports have been the major advantage of African economies and are the lifeblood of global industrial production and construction. However, after 2019, commodity exports considerably declined due to reduced demand resulting from shocks to global economic activities created by the COVID-19 pandemic.

Conversely, we discover that the contribution of clean energy stocks has risen substantially in the long term due to reducing costs, growing acceptance, and deploying clean energy alternatives as viable energy options in recent times.

4.3 Network plots

Our empirical analysis presents graphs with as many as 11 nodes and as many as 112 edges once we introduce other financial assets. For the sole purpose of visual choice, only the thickest edges are shown in the network graphs, while all network statistics are calculated from the full network. For the network plots, we adopt the Gephi open-source software for visualizing and analyzing the network graphs; we also follow the ForceAtlas2 algorithm as



Note(s): The figure reports graphs of overall volatility spillovers between African stock markets and the clean energy market from 2010 to 2021 at different time frequencies

Source(s): Compiled by the authors

Figure 4. Overall volatility spillovers at different time frequencies

implemented in Gephi. Node size, node color, edge thickness, edge arrow size, edge color, and node locations convey more information about the graph (see, Figure 5).

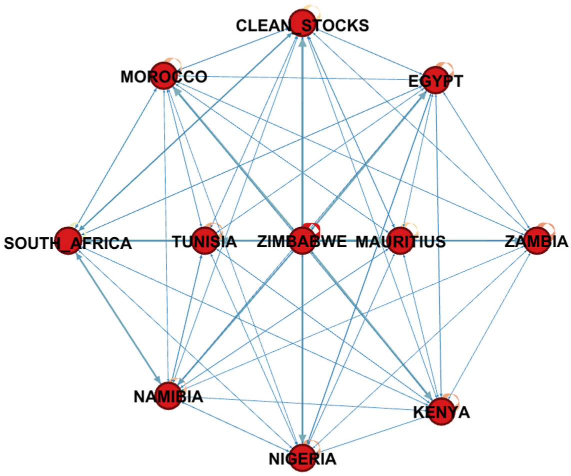
The node sizes indicate each market's contribution to shocks in order of magnitude, while the node color indicates Total Directional Connectedness "To Others." A less influential asset overall will be colored close to dark green, while a highly influential asset will be colored close to dark red, as in the color spectrum in Figure 5. Throughout the dynamic analysis, the thresholds correspond to the 25%, 50%, and 75% percentiles of the "to connectedness" measures of all assets. Hence, node colors are comparable across graphs.

The location of the nodes indicates the strength of average pairwise directional connectedness and is determined by the ForceAtlas2 algorithm, as implemented in Gephi. The algorithm finds a steady state in which nodes that have higher pairwise directional connectedness values are expected to be closer to each other. The edge thickness indicates the average pairwise directional connectedness, and the edge color is lighter for the weakest links and the same for all the others. Since average pairwise directional connectedness is represented by edge thickness, edge color is employed to attain clearer visuals. The edge arrow size from node i to node j increases with the pairwise directional connectedness from node i to node j.

First, we present the network graph for the time domain (TVP-VAR) spillover results in Figure 6. The network graph conveys similar information to that presented in Table 3, with Zimbabwe demonstrating strong influence and significant transmissions to other markets as indicated by the arrows and edge thickness while also demonstrating limited vulnerability. The relative fusion between the markets under consideration is also visible from the graph.

Source(s): Gephi software-ForceAtlas2 algorithm

Figure 5. Color spectrum



Note(s): The figure reports a network plot of overall volatility spillovers between African stock markets and the clean energy market from 2010 to 2021

Source(s): Compiled by the authors

Figure 6. Volatility connectedness between African stock markets and clean energy stocks

Similarly, we also consider the network graph for the frequency domain. Figure 7 presents the network plot across the four frequencies considered in this study following the same procedure explained previously. Evidence presented in the graphs suggests relatively strong volatility connectedness across markets in Freq 1 (The spillover table for band 3.14 to 0.79 roughly corresponds to 1 day to 4 days), with Kenya demonstrating significant contributions to all other markets. However, volatility transmission weakens as we proceed to other frequencies (see Freq 1–4 in appendix).

4.4 Causality results

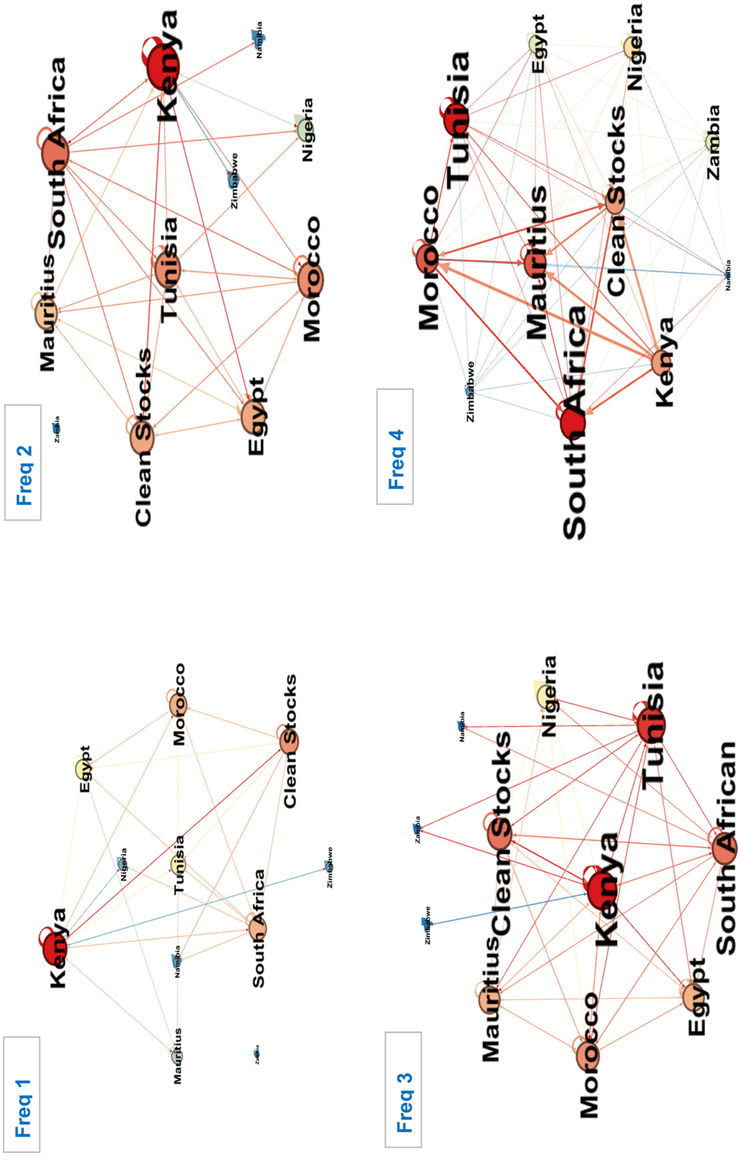
Linking these spillover transmissions to uncertainties due to infectious diseases, it is evident that due to increased financialization, the global financial markets have been empirically shown to be negatively impacted by SARS, EBOLA, & COVID-19 pandemics (see Fasanya *et al.*, 2021b). Notably, the COVID-19 pandemic has led to a global economic slowdown and has grossly affected the African stock markets. Thus, the connectedness across the clean energy and African stock markets may be driven by uncertainties due to infectious diseases. This implies that uncertainty due to the pandemic may induce volatility shocks to the other markets. The possibility of uncertainties due to infectious diseases affecting the volatility spillover between the African stock market and the clean energy market is, therefore, the main thrust of this paper.

Having observed volatility transmissions across the African stock markets and clean energy markets, we examine the role of uncertainties due to infectious diseases on the connectedness between these markets. From a linear perspective, we achieve this by investigating the causal effect of uncertainties due to infectious diseases (EMV_ID) on the total spillover and net spillover for each asset. The results (see Table 4) reveal that EMV_ID's effect is insignificant at the 10% significance level in most cases. This may likely be attributed to the presence of non-linearity in the series.

Furthermore, to confirm our suspicion, we conducted the BDS test developed by Brock *et al.* (1996) to establish the presence of non-linearity in the series. The results (see Table 5) show strong evidence of a non-linear relationship between EMV_ID and each asset's total and net spillovers, as the null hypothesis of serial dependence is rejected at the highest significance levels. Therefore, reliance on the linear Granger-causality test may lead to spurious conclusions as it could have suffered from misspecification errors.

Given the strong evidence of non-linearity, we turn to the results of the quantiles-based causality tests. Figures 8 and 9 summarizes the result of the causality-in-quantiles test conducted for both conditional mean and variance [1]. We present results for both the full sample and the COVID-19 period. Across the board, we find strong evidence supporting rejecting the null hypothesis of no Granger causality for both the full sample and COVID-19 periods. This is in sharp contrast to the results of the linear granger causality test, even though the effect of uncertainties due to infectious diseases on the connectedness between the markets seems more pronounced for the COVID-19 pandemic period when considering the causality-in-conditional mean. Also, the causal evidence is significant mainly in the middle quantiles. However, the causality becomes weak at the extreme quantiles, suggesting that the effect of uncertainties due to infectious diseases on the connectedness between the markets is sensitive to the degree of the performance of both markets. When the markets are performing at their peak, uncertainties due to infectious diseases seem weak in affecting their interactions.

Certain implications could be drawn from our analysis. First, there is evidence of connectedness between the African stock markets and the clean energy market for both time and frequency domains. Second, regarding diversification options, results show that Egypt and Namibia are the best effective portfolio diversification options for investors in the African



Note(s): The figure reports a network plot of overall volatility spillovers between African stock markets and the clean energy market from 2010 to 2021 at different frequencies
Source(s): Compiled by the authors

Figure 7.
Volatility Connectedness between African Stock Markets and Clean Energy Stocks across Frequencies

Linear causality test results (from TVP-VAR) EMV_ID does not granger cause	F-stats	Prob
Total Spillover	0.9308	0.3944
Clean Stocks	15.275***	0.0000
Egypt	2.967*	0.0516
Kenya	1.5864	0.2048
Mauritius	0.3805	0.6836
Morocco	1.6404	0.1941
Namibia	1.6783	0.1869
Nigeria	4.089**	0.0168
South Africa	0.2341	0.7913
Tunisia	0.4289	0.6513
Zambia	0.8096	0.4451
Zimbabwe	0.1097	0.8961

Note(s): This table reports the causality test results for the linear Granger-causality test. The symbols ***, **, * represent a rejection of the underlying null hypothesis that EMV_ID does not Granger-cause each variable considered at the 1%, 5%, and 10% significance levels, respectively
Source(s): Compiled by the authors

Table 4.
Linear causality test results (form TVP-VAR)

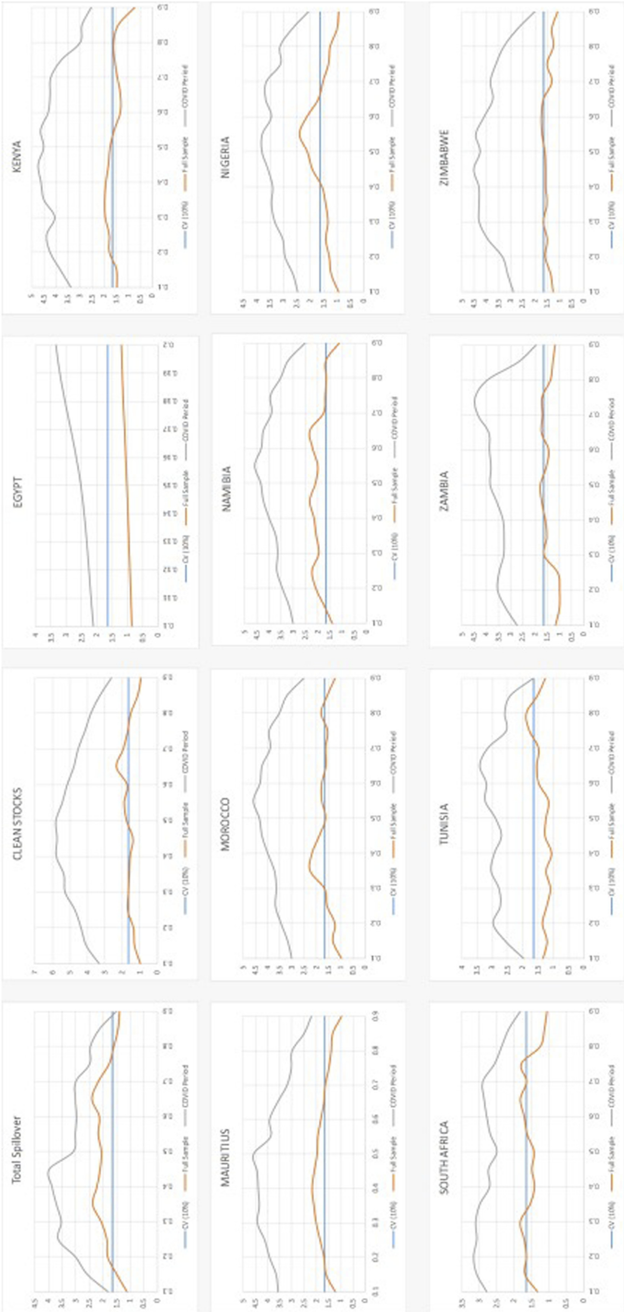
EMV_ID is the causal variable	2	3	4	5	6
Total Spillover	0.1148***	0.2043***	0.2634***	0.2985***	0.3159***
Clean Stocks	0.1135***	0.2017***	0.2599***	0.2944***	0.3117***
Egypt	0.1082***	0.1927***	0.2489***	0.2818***	0.2982***
Kenya	0.1189***	0.2117***	0.2734***	0.3108***	0.3299***
Mauritius	0.1101***	0.1960***	0.2526***	0.2859***	0.3021***
Morocco	0.1081***	0.1922***	0.2479***	0.2809***	0.2972***
Namibia	0.1125***	0.1999***	0.2577***	0.2917***	0.3085***
Nigeria	0.1027***	0.1854***	0.2405***	0.2744***	0.2920***
South Africa	0.1174***	0.2093***	0.2704***	0.3074***	0.3260***
Tunisia	0.1189***	0.2118***	0.2736***	0.3109***	0.3300***
Zambia	0.1136***	0.2021***	0.2605***	0.2948***	0.3117***
Zimbabwe	0.1180***	0.2097***	0.2706***	0.3072***	0.3256***

Note(s): Values in the cell represent the BDS test statistic. The symbols ***, **, * represent the rejection of the underlying null hypothesis of linearity at the 1%, 5%, and 10% significance levels, respectively
Source(s): Compiled by the authors

Table 5.
BDS test results

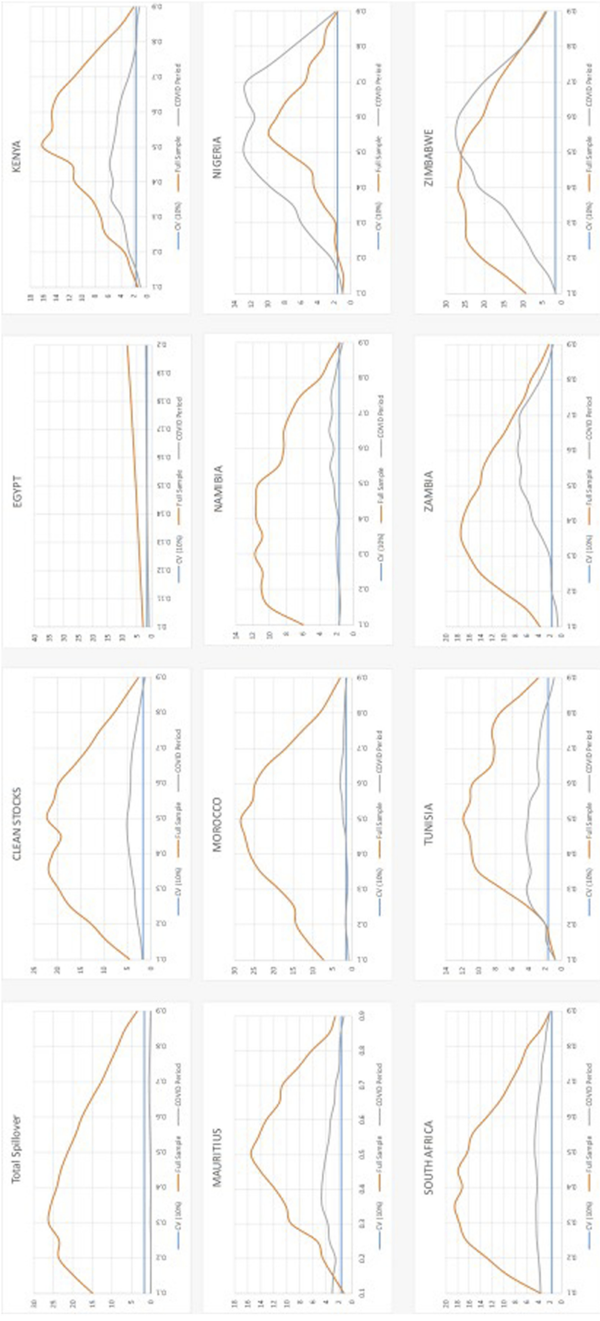
stock markets as they show the weakest vulnerability to idiosyncratic shocks when considering the time domain results. Zimbabwe's dominance can be attributed to the economy's dollarization following a period of hyperinflation. The economy became dollar driven, and since most commodities exports are valued in dollars, there is substantial cause for volatility co-movements.

However, from a frequency domain perspective, Kenya is the most significant contributor of volatility, with its major contribution coming in Freq.4. At the same time, Mauritius is the biggest receiver of volatility spillovers considering all frequencies in our sample. Third, the connectedness among these markets is primarily driven by uncertainties due to infectious diseases. However, the causal effect in most cases seems stronger around the lower and middle quantiles. Fourth, considering non-linearity is crucial when examining the role of uncertainties due to infectious diseases affecting the interactions between both markets.



Note(s): The above figures represent the Causality-in-quantiles in conditional mean. The X-axis reports the quantiles, while the Y-axis reports the t-statistic. CV represents critical value at the 10% level.
Source(s): Compiled by the authors

Figure 8.
Results of causality in conditional-mean



Note(s): The above figures represent the Causality-in-quantiles in conditional variance. The X-axis reports the quantiles, while the Y-axis reports the t-statistic. CV represents critical value at the 10% level
Source(s): Compiled by the authors

Figure 9.
Results of causality in conditional-variance

5. Conclusion and implication for policy

Among historical health crises, the COVID-19 pandemic has been adjudged to have the most devastating effect on financial markets. This has led to numerous studies examining its effect on the financial markets on a country-specific, regional, or global basis. Little or no studies have examined the volatility connectedness between African stock markets and clean energy stocks. Even rarer are studies that consider the response of the connectedness between these markets to a health crisis. Findings from recent studies have determined factors that cause volatility spillovers among financial markets. Accordingly, it is reasonable to propose that pandemics might not only affect the performance of a financial market but also have severe implications in terms of cross-market risk relationships altering asset prices and investors' risk preferences.

In addition to methodological advancements, this study makes the following contributions. First, this paper examines the dynamic connectedness between African stock market indices and clean energy stocks using two approaches, the Time-Varying Vector Autoregression (TVP-VAR) for the time domain and Barunik and Krehlik (2018) for the frequency domain. Second, we provide insights into the causal impact of uncertainties due to infectious diseases (EMV_ID) on this relationship.

The findings of this study are summarized as follows. First, we find evidence of strong connectedness between the African stock markets and the clean energy market for both time and frequency domain approaches. Second, regarding diversification options, results show that Egypt and Namibia are the best effective portfolio diversification options for investors in the African stock markets as they show the weakest vulnerability to idiosyncratic shocks when considering the time domain results. Kenya contributes the most volatility for the frequency domain, with its significant contribution coming in the long run. Also, Mauritius is the biggest receiver of volatility spillovers considering all frequencies in our sample. Third, the causal analysis provides evidence supporting a non-linear causal relationship between uncertainties due to infectious diseases and the connectedness between both markets, mostly at lower and median quantiles. This reflects the disturbing effects of uncertainties due to infectious diseases, which matters to the formulations of policies seeking to achieve stability. Like results reported by Adekoya and Oliyide (2021), this study provides evidence of a global financial cycle channel during the COVID-19 pandemic. The occurrence of the pandemic and the speculative and sentimental attitude of policymakers and investors essentially drives this channel. Our conclusion complements the emerging literature on the vulnerability of the stock markets to uncertainties due to health crises.

Several important policy implications can be drawn from our findings. First, the robust interconnectivity between African equity and clean energy markets underscores the importance of encouraging regional cooperation among African nations. This may include exchanging information, harmonizing policies, and promoting cross-border investments. Such collaboration can enable African countries to capitalize on the potential of clean energy, establish a more resilient financial system, and bolster their ability to withstand external shocks. Second, with Egypt and Namibia identified as the most effective diversification choices for investors in African equity markets, policymakers should draw investments into these nations and encourage a more equitable investment distribution throughout the continent. This would minimize the region's susceptibility to economic disturbances and improve financial stability. Third, Kenya was identified as the primary contributor to long-term volatility. Policymakers in Kenya and other African nations should contemplate adopting measures to mitigate this volatility and establish a more stable investment environment by enhancing market transparency, fortifying the regulatory structure, and advocating for sustainable and responsible investment practices.

Governments must improve their preparedness for future health emergencies by investing in healthcare, strengthening early warning systems, and promoting efficient coordination during crises. Policymakers should focus on reinforcing financial systems, implementing policies for economic resilience, and introducing social protection measures to support vulnerable communities and boost economic recovery. As part of future research, it would be interesting to extend the study to the risk associated with other financial assets such as cryptocurrencies, and real estate, particularly examining the effects of Africa-based Economic policy uncertainty and uncertainties due to infectious diseases will further enrich the extant literature.

Note

1. The tabulated results available are available on request from the authors

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Further reading

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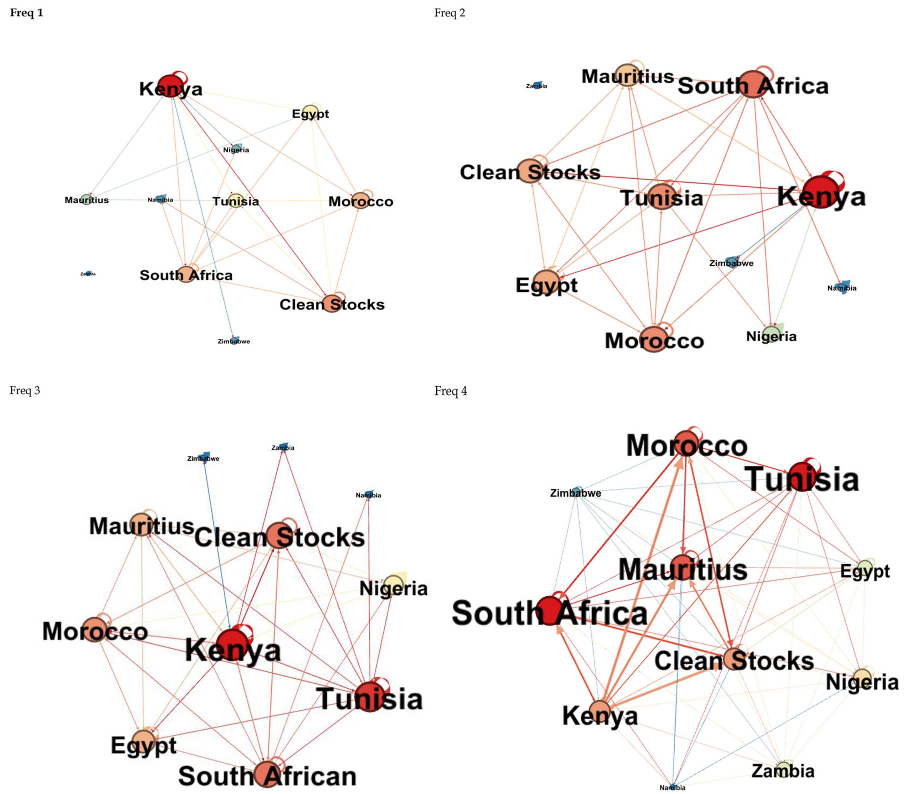
Appendix

Volatility connectedness between African stock markets and clean energy stocks across frequencies (as shown in Figure 7)



Source(s): Compiled by the authors

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