The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/1746-8809.htm

Connectedness across commodities, stocks, exchange rates and bonds markets in Africa: the Covid-19 pandemic case

Received 19 March 2023
Revised 16 June 2023
27 October 2023
Accepted 14 December 2023

Robert Owusu Boakye
Banking and Finance Department, University of Professional Studies, Accra, Ghana
Lord Mensah
Department of Finance, University of Ghana, Business School, Accra, Ghana
Sanghoon Kang
PNU Business School, Pusan National University, Busan, South Korea, and
Kofi Osei
Department of Finance, University of Ghana, Business School, Accra, Ghana

Abstract

Purpose – The study measures the total systemic risks and connectedness across commodities, stocks, exchange rates and bond markets in Africa during the Covid-19 pandemic.

Design/methodology/approach – The study uses the Diebold-Yilmaz spillover and connectedness measures in a generalized VAR framework. The author calculates the net transmitters or receivers of shocks between two assets and visualizes their strength using a network analysis tool.

Findings – The study found low systemic risks across all assets and countries. However, we found higher systemic risks in the forex market than in the stock and bond markets, and in South Africa than in other countries. The dynamic analysis found time-varying connectedness return shocks, which increased during the peak periods of the first and second waves of the pandemic. We found both gold and oil as net receivers of shocks. Overall, over half of all assets were net receivers, and others were net transmitters of return shocks. The network connectedness plot shows high net pairwise connectedness from Morocco to South Africa stock market.

Practical implications – The study has implications for policymakers to develop the capacities of local investors and markets to limit portfolio outflows during a crisis.

Originality/value – Previous studies have analyzed spillovers across asset classes in a single country or a single asset across countries. This paper contributes to the literature on network connectedness across assets and countries.

Keywords Africa, COVID-19, Commodities, Stocks, Exchange rates, Bonds, Systemic risks, Network connectedness

Paper type Research paper

1. Introduction

The COVID-19 pandemic and its associated oil price shocks have adversely affected the global economy, including commodities and financial assets (Baker *et al.*, 2020). In April 2020, Africa reported 6,194 COVID-19 cases and 242 deaths across 47 countries (WHO, 2020). In response, African governments implemented various measures such as lockdowns, travel bans, and school closures to curb the virus's rapid spread. The unpredictable nature of the pandemic led to heightened market volatility and uncertainties, with ongoing downside risks. During periods of high uncertainty, the financial market's interdependence increases, generating connectedness across assets or markets (Longin and Solnik, 2001; Lin *et al.*, 1991;

Since submission of this article, the following author(s) have updated their affiliations: Lord Mensah is a visiting Professor at the Ghana Institute of Management and Public Administration Business School.

1746-8809
DOI 10.1108/IJOEM-03-2023-0411

Roll, 1989). Measuring and monitoring the magnitude and direction of such connectedness provide useful information for portfolio investors, policymakers and risk management practitioners (Diebold and Yilmaz, 2015; Awartani and Maghyereh, 2013). For example, portfolio investors can use the size of the total systemic risks and the net directional spillovers to achieve higher portfolio diversification. Policymakers may also rely on such information to formulate fiscal and monetary policies to safeguard employment and the financial system.

The COVID-19 pandemic triggered an economic and financial crisis, occasioned by the US stock market crash on March 23, 2020, when the US Senate's failure to pass a $2bn COVID-19 economic relief package. The crash had a global impact, with major stock market indexes worldwide, including Africa, experiencing significant declines. For instance, the S&P 500 dropped by 2.9%, while the Dow and Nasdaq fell by 3.7% and 1.5%, respectively. Additionally, many African countries saw their currencies depreciate by an average of 8% against the US dollar, as reported by the African Financial Market Index (AFMI) in 2020. During the same period, crude oil (brent) prices reached a historic low of $23.43 per barrel in November 2002. On the contrary, gold prices have reached a record high of almost $2,000 per ounce. Other financial markets also saw variable pandemic-related developments. For instance, South Africa witnessed a rise in government bond yields occasioned by Moody's downgrade in March 2020.

Studies (Tiwari *et al.*, 2020; Arfaoui and Ben Rejeb, 2017; Beckmann and Czudaj, 2013 among others) have shown that due to increased financial integration, gold and oil have assumed both commodity and financial attributes, making them, along with other financial assets, important factors in financial markets volatility. Increasing global stock markets integration has limited diversification opportunities in the stock markets, pushing investors to find alternative investments such as oil and gold (Lahiani and Jlassi, 2021; Morema and Bonga-Bonga, 2020; Gao *et al.*, 2020; Bakas and Triantafyllou, 2020; Billio *et al.*, 2017). Portfolio investors and managers may also rebalance their portfolios by switching from more risky assets to less risky assets (Baele *et al.*, 2020).

In recent times, studies on market interdependence, risk spillovers and connectedness have become important topics for academicians and portfolio investors, especially after the global financial crisis, to understand the correlation dynamics between commodities and financial assets. However, most of these studies have concentrated on using few assets (Kang and Lee, 2019; Zhang *et al.*, 2017; Khalfaoui *et al.*, 2015). Some of the studies have focused on estimating the net total directional spillovers between a particular market and the entire network of markets (Atenga and Mougoué, 2021a; Gourène *et al.*, 2019b; Gourène *et al.*, 2019a). Others have focused on advanced countries and markets (Polat, 2022; Bouri *et al.*, 2021). Few studies in Africa have analyzed return or volatility spillovers across different asset classes in a single country (Morema and Bonga-Bonga, 2020; Duncan and Kabundi, 2013).

According to Diebold and Yilmaz (2015), studying risk spillovers and connectedness of one asset class across different countries leaves aside the connectedness across asset classes within the same country. On the other hand, measuring the connectedness across different asset classes within a single country also leaves aside the connectedness of a single asset across different countries and how it affects the connectedness of different assets within the same country. Without the interaction between connectedness across assets and country, portfolio investors, risk managers and policymakers will need to include the source of the connectedness that will have serious implications on other types of assets.

In this study, we contribute to the literature on network connectedness by estimating the return shock spillovers across commodities, stocks, exchange rates and bonds in six Africa countries. We apply the Diebold and Yilmaz (2012, 2014, 2016) which blends the generalized VAR variance decomposition theory and network topology theory by Newman (2010). This method can measure the total system-wide connectedness (systemic risks) by aggregating spillover effects across assets and countries into a single value. It can also capture both static and time-varying connectedness, and total and pairwise directional spillovers. Other correlation-based techniques, such as the dynamic conditional correlation (DCC) model introduced by Engle (2009) and the equi-correlation approach by Engle and Kelly (2012), have been used in the literature to measure the association between two variables. However, it measures only linear dependence and non-directional association. Our approach can measure pairwise directional connectedness and the time-varying connectedness, unlike the high state/low volatility spillovers indicator of Edwards and Susmel (2001). The Conditional Value-at-Risk (CoVaR) approach introduced by Adrian and Brunnermeier (2001) and the Marginal Expected Shortfall (MES) approach by Acharya *et al.* (2010, 2012) only focused on the correlation between a firm and the overall market movements in one direction or the other. Our method empirically measures connectedness from pairwise to system-wide. Consequently, the study measures (1) the total systemic risks, both statically and dynamically, (2) the size and the total and pairwise directional spillovers, and (3) net spillover contributors and receivers of return shocks for the period.

We focus on Africa and the COVID-19 crisis period for some reasons. First, according to data compiled by Johns Hopkins University, Africa was the less deadly region during the pandemic, making the region less risky than other regions in terms of human lives and investments. However, Africa witnessed a reverse of portfolio flows from a net inflow of $23bn in 2019 to a net outflow of $27bn in 2020, according to the African Development Bank's 2021 economic outlook report, as a result of global investors becoming risk-averse. Second, according to the Brookings Institute, Africa, despite COVID-19, is still an attractive investment destination for international investors and will have a combined consumer spending of about $6.7tn by 2030. Third, a survey published in March 2020 by the African Private Equity and Venture Capital Association (AVCA) found a marked shift in private equity (PE) investment destinations on the continent. Most of the previous PE deals occurred in southern Africa. According to limited partners (LPs) that participated in the survey pointed to West Africa as the most attractive region for investments over the next three years. However, general partners (GPs) identified East Africa and Kenya as the most potential places for investment over the same period. Fourth, previous studies on spillovers and market interdependence have concentrated on a single market across different countries. Studies that focused on stock markets include (Boako and Alagidede, 2017, 2018; Sugimoto *et al.*, 2014) and foreign exchange markets (Boakye *et al.*, 2023; Atenga and Mougoué, 2021b; Owusu Junior *et al.*, 2017; Carsamer, 2016). Finally, there is a dearth of literature on network connectedness across assets and countries in Africa.

The remainder of the paper is organized as follows: Section 2 presents the literature review. Section 3 presents the methodology. Section 4 presents the data and descriptive statistics. Section 5 presents the empirical results and discussions, and Section 6 presents the conclusion and policy implications.

2. Literature review

Early studies (King *et al.*, 1994; Hamao *et al.*, 1990; King and Wadhwani, 1990) on return or volatility spillovers and market interdependence of international markets found that both return and volatility emanated from US stock markets to the rest of the world during crisis periods. Financial, economic and health crises have recently spurred studies on risk spillovers and connectedness, particularly after the global financial crisis (GFC). For instance, Xu *et al.* (2019) used Diebold and Yilmaz (2012) spillover index and Baruník *et al.* (2017) asymmetric volatility model to investigate the time-varying asymmetric volatility spillover between the oil and stock markets of China and the US during the GFC. The study found time-varying volatility spillover between oil and stock markets, and their interdependence increased during GFC. The study also found an asymmetric spillover effect between oil and stock markets. Mensi *et al.* (2021) employed Diebold and Yilmaz (2012) and Baruník *et al.* (2017)

asymmetric volatility model to examine the dynamic frequency spillover and connectedness between oil and stock of MENA countries during recent crises. They found time-varying volatility spillovers between oil and the stock markets considered. The short-term spillovers are higher than intermediate-term, with the highest jump occurring during the COVID-19 pandemic, followed by GFC. Spillovers are higher in oil-exporting than in oil-importing countries in the sample. Saudi Arabia, Qatar and UAE were found to be net contributors to volatility shocks in the short and intermediate terms. However, Oil, Egypt, Morocco and Turkey stock markets are net receivers.

Some authors have also employed dynamic conditional and systemic risk measures to analyze the interdependence of markets. Mezghani and Boujelbène-Abbes (2021) used a time–frequency connectedness framework by Barunik and Krehlik (2018), and the BEKK-GARCH models to investigate the impact of financial stress on the dynamic connectedness and hedging for the oil market and stock-bond markets of GCC countries from January 2007 to December 2018. They found that the correlation between the oil and stock-bond markets tends to be stable in non-shock periods, but it evolves during oil and financial shocks at lower frequencies. Moreover, they found that the oil market and financial stress are the main transmitters of risks. Wen *et al.* (2020) used VAR-BEKK-GARCH (1,1) and VaR framework to investigate the information transmission channels between gold and financial assets in the US. They found the mean spillover effect of gold on the financial assets except for the stock market. They also found no significant volatility spillover between gold and oil but found a significant spillover between US stocks and forex markets. Yavas and Rezayat (2016) employed GARCH and multivariate auto-regressive moving averages (MARMA) to investigate the linkages among equity exchange-traded funds (ETF) returns and transmission of volatilities in the USA, Europe and key emerging countries' stock markets between February 2012 and February 2014. They found the existence of significant co-movement of returns among all country ETFs. They also found that no ETF volatility is transmitted from the sample countries to the USA, Brazil, China and South African stock markets. Again, US market volatility is transmitted to India, Russia, Mexico and Turkey, while European volatility spills over to Mexico and South Korea. Bagchi (2017) used the Asymmetric Power ARCH (APARCH) model to examine the dynamic relationship between crude oil price volatility and stock markets in emerging economies, like Brazil, Russia, India and China between July 2009 and January 2006. He found that, for Bovespa, MICEX, BSE Sensex and crude oil, there is an asymmetric response of volatilities to positive and negative shocks. He also found the existence of a negative correlation between returns and volatility. Again, the results suggest the presence of long memory behavior and persistent volatility clustering phenomenon amongst the BRIC countries' crude oil prices and stock markets. Jeribi and Ghorbel (2021) used generalized autoregressive score (GAS), GO-GARCH and VaR models to forecast the risk of the five leading cryptocurrencies, stock market indexes (developed and BRICS) and gold returns, conduct different backtesting procedures forecasts and to the hedging potentials of cryptocurrencies and gold. They found that Bitcoin has the highest VaR among cryptocurrencies and gold, and the BRICS index returns are lower than developed countries. They also proved that Bitcoin and gold can hedge the risks in developed stock markets. Bitcoin can be considered the new gold for these economies.

Other scholars have also applied the Diebold – Yilmaz index and wavelet correlation techniques. Mensi *et al.* (2020) used Diebold and Yilmaz (2012) spillover index and wavelet techniques to examine co-movements, risk spillovers and portfolio implications between precious metals and energy returns. The study found dynamic volatility among markets that intensified during the GFC and ESDC. Gold and Oil were net transmitters of volatility, while other markets were net receivers. Rubbaniy *et al.* (2022) used wavelet methods to investigate the safe-haven properties of soft commodities during the COVID-19 pandemic. The results show that staple soft food commodities (corn, wheat, cotton and cocoa) are positively correlated with the global COVID-19 fear index. They also found staple soft commodities as safe-haven assets.

Some studies have also investigated the effects of COVID-19 on commodities and financial markets and how these markets are connected during turbulent periods using different techniques. For example, Farid *et al.* (2021) used MCS-GARCH and Diebold and Yilmaz (2012) to examine the volatility connectedness network of equities and major commodities in the US. They found stocks and gold as the largest net-contributor of volatility shocks during the COVID-19 pandemic. They found the US stock market as the sole net contributor of shocks to the commodities market. They found reduced portfolio diversification and hedging opportunities for investors across alternative asset classes. The study further found natural gas as a safe-haven asset. Bouri *et al.* (2021) assessed the changes in the structure and time-varying pattern in the connectedness across various asset classes during the COVID-19 pandemic in the US using TVP-VAR and Granger causality analysis. They found evidence of strong spillover effects in the financial markets. The study found that the MSCI world and USD index were net transmitter shocks in the pre-COVID-19 periods, whereas the bond index became the main net transmitter after the COVID-19 pandemic. However, the USD index was a net receiver throughout the pandemic period. Abuzayed and Al-Fayoumi (2021) used CoVaR and Marginal Expected Shortfall to examine the effects of oil price shocks on the stock returns of GCC countries. They found oil price shock spillover effects on GCC stock returns. Oil price shock effects on stock returns were less before than during the pandemic. Liao *et al.* (2021) used Diebold and Yilmaz (2014) to explore the spillover effects among oil, gold and 16 major stock markets under four health crisis periods. The results show that COVID-19 generated significant return and volatility spillover effects across oil, gold and stock markets. They found return insensitive, while volatility spillovers were highly sensitive to the pandemic, with return and volatility being more intense during the COVID-19 period. Again, they found oil as a net transmitter and gold net receiver of risks. Polat (2022) used both Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) indexes to analyze the systemic risks contagion across the euro area. They found the systemic risks increased during major financial crises but were at a maximum during the Covid-19 pandemic. The Baruník and Křehlík index also found a rise in the systemic risk during the GFC and COVID-19 periods. They found that the size of the directional spillovers rose during the GFC and COVID-19 crises.

Some African country-specific studies have investigated the correlation and interdependence among markets using different methods. For instance, Duncan and Kabundi (2013) used Diebold and Yilmaz (2012) to characterize domestic and foreign sources of volatility transmission for South African bonds, commodities, currencies and equities. The study found time-varying domestic and foreign spillovers across asset classes in South Africa and with the global capital markets. The linkages strengthened during GFC. Domestic volatility spillover across assets was larger than foreign volatility shocks received from VIX. Morema and Bonga-Bonga (2020) employed VAR and DCC-GARCH models to investigate the impact of commodities (oil and gold) price fluctuations on the South African stock market. The study found unidirectional volatility transmission between commodities and stock markets. The study also found gold to be a safe haven asset than stocks. Akhtaruzzaman *et al.* (2022) also applied the DCC, VaR and, Diebold and Yilmaz (2012) spillover index to examine how risks spillover from US financial firms and banks to some African financial firms during the Covid-19 crisis. They found that the downside risk exposures of African financial firms and banks increased significantly between Jan and April 2020. The nature and magnitude of the downside risks in the US market were similar to that of African markets. They further found the US market to be a net transmitter of risk spillover, and African countries are net receivers. Fasanya and Oyewole (2023) applied the time-varying volatility connectedness framework of Antonakakis *et al.* (2020) and the frequency-domain volatility connectedness framework of Barunik and Krehlik (2018) to examine the dynamic connectedness between African stock market indices and clean energy stocks from November 2010 to August 2021. They found evidence of strong connectedness between the African stock markets and the clean energy market but weak in the short and medium investment horizon. They also found evidence of a nonlinear causal relationship between uncertainties due to infectious diseases, and the connection between both markets, mostly at lower and median quantiles.

3. Methodology

We follow scholars such as Mensi *et al.* (2021), Mezghani and Boujelbène-Abbes (2021) and Yoon *et al.* (2019), and use return of all assets (commodities, exchange rates, stocks and bonds) for our analysis. We calculate the returns by taking the difference in the logarithm percentage of two consecutive prices $R_t = ln\,(M_t/M_{t-1})$ where R_t is the return of an asset, M_t and M_{t-1} are the daily closing prices of the asset at time t and $t-1$, respectively. We then use the Diebold and Yilmaz connectedness model to estimate the total system-wide connectedness (both statically and dynamically) and the net directional spillovers. The model works in a generalized vector autoregressive environment, developed by Koop *et al.* (1996) and Pesaran and Shin (1998). We proceed as follows. Consider a covariance stationary p^{th}-order $VAR(p)$ model,

$$x_t = \sum_{i=1}^{p} \Theta_i x_{t-1} + \varepsilon_t, \tag{1}$$

where x_t is an $(n \times 1)$ vector of return series with non-orthogonal shocks, Θ_i is an $(n \times n)$ parameter matrix, and ε_t is an $(n \times 1)$ vector of the error term. By covariance stationary, the moving average (MA) representation of the VAR process exists, and it is given by:

$$x_t = Q(L)\varepsilon_t, \varepsilon_t \sim (0, \Sigma) \tag{2}$$

where $Q(L) = Q_0 + Q_1 L + Q_2 L^2 + \ldots + Q_p L^p$ and $E(\varepsilon_t \varepsilon_t') = \Sigma$. Q_0 is an $(n \times n)$ identity matrix with $Q_i = 0$ for $i < 0$. The entries of the H-step-ahead generalized vector autoregressive (GVAR) matrix of market j contribution to market i forecast-error variance is given by:

$$\widetilde{d}_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' Q_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' Q_h \sum Q_h' e_i\right)}, \tag{3}$$

where e_j is a selection vector with ones as the j^{th} element and zeros elsewhere, Q_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR, Σ is the covariance matrix of the shocks vector in the non-orthogonalized VAR, σ_{jj} is the j^{th} diagonal element of Σ. In the GVAR framework, shocks are not necessarily orthogonal, so the sum of forecast error variance is not equal to one. The generalized connectedness measure, denoted by D^g, is based on $\widetilde{D}^g = [\widetilde{d}_{ij}^g]$, not D^g, where $\widetilde{d}_{ij}^g = \frac{\widetilde{d}_{ij}^g}{\sum_{j=1}^{N} \widetilde{d}_{ij}^g}$ is each row sum of D^g normalized to one. By construction, $\sum_{j=1}^{N} \widetilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^{N} \widetilde{d}_{ij}^g = N$. The non-diagonal elements of matrix $\widetilde{d}_{ij}^g$ are used to calculate the total system-wide connectedness, net total and pairwise directional spillovers of return shocks. To calculate the pairwise directional spillover between assets i and j, we denote the pairwise directional spillover from asset j to i by $\theta^H_{i\leftarrow j} = d^H_{ij}$. Similarly, the pairwise directional spillover from market i to j is $\theta^H_{j\leftarrow i}$. Thus, the net pairwise directional connectedness is given as:

$$\theta^H_{ij} = \theta^H_{i\leftarrow j} - \theta^H_{j\leftarrow i}. \tag{4}$$

Net pairwise spillovers allow us to determine whether an asset is a transmitter or recipient of return shocks between the two assets.

Next, we can aggregate partially to determine how much return shocks all other assets transmit to assets i. This is represented by $\theta^H_{i\leftarrow \bullet}$, and it is computed as:

$$\theta^H_{i\leftarrow \bullet} = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{d}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{d}^g_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{d}^g_{ij}(H)}{N} \times 100. \tag{5}$$

Similarly, we calculate how much returns shocks asset i transmit to all other assets, and it is given as:

$$\theta^H_{\bullet\leftarrow i} = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{d}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{d}^g_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1\\ j\neq i}}^{N} \tilde{d}^g_{ji}(H)}{N} \times 100 \tag{6}$$

Sometimes, we are interested in determining whether an asset is a net-transmitter or net-recipient return shocks among other assets. Consequently, we can calculate the net total directional spillover ("To" and "From") as:

$$\theta^H_{i} = \theta^H_{\bullet\leftarrow i} - \theta^H_{i\leftarrow \bullet}. \tag{7}$$

Finally, we compute the total system-wide spillover, which is the total uncertainties within the market in the period under consideration. This is given as:

$$\theta^H = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \tilde{d}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{d}^g_{ij}(H)} \times 100 = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N} \tilde{d}^g_{ij}(H)}{N} \times 100. \tag{8}$$

To develop the network connectedness, Diebold and Yilmaz (2014, 2016) interpreted the variance decomposition matrix as an adjacency matrix of weighted directed networks. The elements of the adjacency matrix are our pairwise directional spillovers, $\theta^H_{i\leftarrow j}$ or $\theta^H_{j\leftarrow i}$. The row sum of the adjacency matrix gives the total directional "From" connectedness, which is sometimes called "From-degrees" in network literature, denoted by $\theta^H_{i\leftarrow \bullet}$; and the column sum of the adjacency gives the total directional “To” connectedness, which is sometimes called “To-degrees”, denoted by $\theta^{H}_{\cdot\leftarrow i}$; the mean degree is our total system-wide connectedness, denoted by θ^{H}. The mean degree is key to the connectedness measure.

4. Data and descriptive statistics

4.1 Data

We use the return series from the daily closing spot prices of crude oil, gold, stocks, and foreign exchange against the US dollar and 10-year government bond yield. Because of the objectives of the study and data availability, our data set covers the period from 4 November 2019 to 3 July 2021. The sample period gives us an idea of the total systemic risks at the onset and during the pandemic, as shown in Figure 2. We consider assets from six (6) major African countries: South Africa, Morocco, Kenya, Nigeria, Mauritius, and Namibia. These countries, except Namibia, are part of seven African stock exchanges that list about 2,000 companies with a total market capitalization of about $ 1.5tn. Mauritius is one of the two countries to be added to the African Exchange Linkages Program (AELP) in the second phase. Namibia has well-developed local investors and a high concentration of pension funds. In choosing the countries, we considered the need to have the same start and end dates. We also included two commodities, Brent crude oil and gold. Like Bagheri and Ebrahimi (2020) and Marobhe (2022), all our data were taken from investing.com. Throughout the paper, ZAR, MAD, KES, NGN, MUR and NAD refer to the South African rand, Moroccan dirham, Kenyan shillings, Nigerian naira, Mauritian rupee and Namibian dollar, respectively, against the US dollar. JSE, CSE, KSE, NGX, MSE and NSE represent South Africa, Morocco, Nairobi, Nigerian, Mauritius and Namibian stock markets index. RSA_10 yr, MOR_10 yr, KEN_10 yr, NIG_10 yr, MAU_10 yr and NAM_10 yr are the 10-year government bonds of South Africa, Morocco, Kenya, Nigeria, Mauritius and Namibia, and oil (Brent crude oil) and gold represent the commodities market.

4.2 Data descriptives

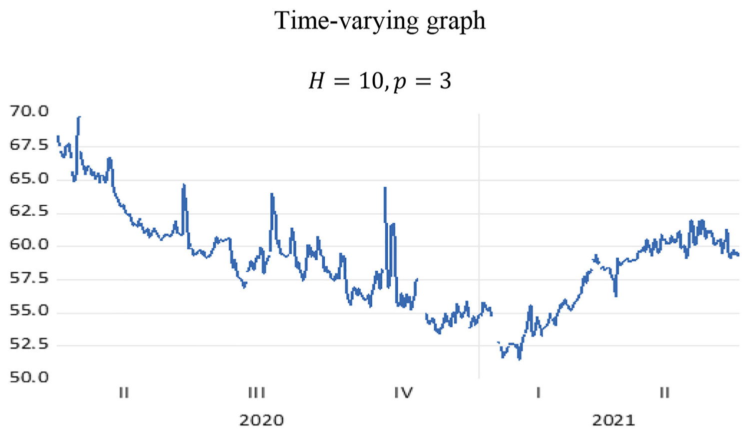
Figure 1 shows the trends of daily closing prices of some of the assets in this study together with their returns on the same graph (**see appendix for the rest of the assets**). We observed that following the 23 March 2020 US stock market crash, some assets reacted to this market event or shock. For instance, crude oil prices initially fell but recovered quickly and trended upwards, whereas gold trended upward at the onset and during the pandemic. The bond markets saw similar price fluctuation following the large withdrawal of portfolio investments by investors and the inability of many African governments to access the international credit market following the downgrade of African bonds by the international credit rating agencies.

Table 1 reports the descriptive statistics of the assets returns. Most of the assets recorded positive returns as indicated by the mean values, except the Moroccan dirham and the bond markets of Morocco, Nigeria and Mauritius. The Nigerian stock recorded the highest returns of 8.22% during the period. All the assets recorded positive returns in the currency market except the Moroccan dirham. All stocks also recorded positive returns, although the Covid-19-induced financial crisis originated from the US stock market. South Africa, Kenya and Namibia recorded positive returns in the bond market, while Morocco, Nigeria, and Mauritius recorded negative returns. Both gold and oil also recorded positive returns. The Namibian stock market and Brent crude oil returns were more volatile for the period under consideration as they recorded the highest standard deviation of 9.3256 and 3.3291, respectively. All the asset returns deviate from the Gaussian normal distribution, as shown by the probability values of the Jarque-Bera test. The results of the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) tests indicate that the return series is stationary at a 1% significance level.

Note(s): On each graph, the brown represents the asset prices over time, and the blue represents return volatility
Source(s): Figure by authors (2023)

Figure 1.
Dynamics of asset prices and their return volatility series

Table 2 shows the unconditional correlation matrix among the asset returns. We observe that oil and gold are weakly correlated to stocks, forex and bonds. However, we noticed a strong positive correlation (0.94) between the South African rand and the Namibian dollar, followed by the Moroccan dirham and the Namibian dollar (0.26%), and the South African rand and



Source(s): Figure by authors (2023)

Figure 2. Dynamic return connectedness across all assets and countries

the Moroccan dirham (0.25%). According to Pukthuanthong and Roll (2009) and Ragunathan (1999), correlations are insufficient for making inferences about market integration or interdependence.

5. Results and discussions

5.1 Static return connectedness

Table 3 presents the static return connectedness across all assets and countries. The total system-wide (systemic risks) is 21.50%. The low measure indicates weak or low connectedness among the assets and implies higher diversification opportunities in African financial markets. It also indicates a lower contagion effect during the pandemic, where shocks from one asset or market trigger widespread negative sentiment and panic in others. On the total directional spillovers, the South African rand contributed the highest, 65.2%, to the shocks in all other assets and countries. The lowest contributor of return shocks in other assets is the Mauritius bond market, 5.2%.

On the other hand, the Namibian dollar received the greatest shocks, 54.6% from all other assets, followed closely by the South African rand, 54.5%. Morocco's bond market received the least shocks (7.8%), followed by the Namibian stock market (8.1%). Between the two commodities (gold and oil), gold transmitted the least (16.2%) return shocks and also received the least (23.2%) from other assets. Most assets have a higher pairwise connectedness to oil than gold. Stocks in all the countries are more connected to oil than to gold.

A high pairwise connectedness between two assets or countries can highlight the strong ties between the two assets or countries. There is a high pairwise connectedness (42.3%) from the South African rand to the Namibian dollar; the reverse is 41.7%. This is because South Africa and Namibia are trade partners. Namibia exports about 27% of its total exports to South Africa. In the intra-market pairwise connectedness, we observe a high pairwise connectedness from the Moroccan stock market to the South African stock market (9.4%). This is because their stock markets are attractive and easily accessible to international investors because of their market transparency and enforceability of standard financial markets master agreements. There is also easy access to foreign exchange in both countries. Similar reasons can be adduced to the high pairwise connectedness from South Africa to the Mauritius stock market (6.4%) and that from the Mauritius stock market to the Moroccan stock market (6.4%).

Table 1. Descriptive statistics of asset returns

	OIL_BRENT	GOLD	ZAR	MAD	KES	NGN	MUR	NAD	JSE	CSE
Mean	0.0534	0.0299	0.0141	−0.0080	0.0164	0.0536	0.0309	0.0144	0.0535	0.0263
Median	0.2787	0.0572	−0.0315	−0.0112	0.0000	0.0000	0.0000	−0.0494	0.1052	0.0358
Maximum	19.0774	5.6266	3.9558	1.7848	0.9321	19.5309	3.7286	3.7893	9.0570	5.3054
Minimum	−27.9762	−5.0734	−2.8438	−1.9878	−1.5899	−3.2790	−2.3769	−2.8991	−10.4504	−9.2317
Std. Dev	3.3291	1.2139	0.9812	0.3045	0.1969	0.9429	0.6018	0.9494	1.5266	0.9335
Skewness	−1.7763	−0.2851	0.4821	0.1699	−1.1100	17.5793	0.5312	0.4105	−0.6983	−2.6883
Kurtosis	24.2722	6.6370	3.7189	9.0363	15.1910	348.5588	7.8212	3.6060	13.4974	32.1227
Jarque-Bera	10445.97 **	304.3814 **	32.48415 **	820.9055 **	3448.48 **	2709530 **	547.3727 * *	23.38774 **	2518.6 **	19696.9 **
ADF	−20.7864 **	−24.03 **	−14.9407 **	−21.6281 **	−15.9017 **	−26.5158 * *	−18.0925 **	−23.2508 * *	−7.9052 **	−19.4973 **
PP	−20.8713 **	−24.6614 **	−24.2788 **	−21.9611 **	−15.5028 **	−26.5991 **	−36.2306 **	−23.2722 **	−25.583 **	−19.5573 **
Observations	539	539	539	539	539	539	539	539	539	539

	KSE	NGX	MSE	NSE	RSA_10YR	MOR_10YR	KEN_10YR	NIG_10YR	MAU_10YR	NAM_10YR
Mean	0.0214	0.0822	0.0007	0.0333	0.0129	−0.0412	0.0109	−0.0340	−0.1360	0.0087
Median	0.0388	0.0173	0.0164	0.1036	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	3.8116	5.9152	10.2660	150.8270	9.8095	7.9677	6.5300	20.3526	9.0452	11.8817
Minimum	−5.6718	−5.6982	−10.1039	−148.2463	−5.6297	−13.1303	−6.5300	−20.4902	−26.0193	−14.6427
Std. Dev	1.0735	1.0170	1.0764	9.3256	1.1915	1.0306	1.7864	2.6847	1.5960	2.7037
Skewness	−0.7357	0.4301	−1.4228	0.3822	1.2460	−3.7914	−0.0757	−0.7358	−8.2238	−0.0066
Kurtosis	7.3017	10.8238	44.4470	246.3459	18.0872	64.9972	4.0378	27.2815	137.5645	9.2143
Jarque-Bera	464.2182 **	1391.342 **	38761.98 **	1329933 **	5251.532 **	87613.33 **	24.70151 **	13289.91 **	412742.2 **	867.3025 **
ADF	−17.6324 **	−11.9064 **	−11.2988 **	−17.9014 **	−20.9418 **	−21.6495 **	−17.2117 **	−23.723 **	−14.5235 **	−17.8191 **
PP	−17.2284 **	−18.3836 **	−17.4928 **	−80.9024 **	−21.2889 **	−21.6394 **	−74.8205 **	−24.427 **	−23.4243 **	−31.723 **
Observations	539	539	539	539	539	539	539	539	539	539

Note(s): The table summarizes the returns of all the assets. JB is the Jarque-Bera test for normality. ADF (PP for Philip-Perron) is the Augmented-Dickey Fuller test for stationarity in the return series. *** indicates statistical significance at the 1% level
Source(s): Table by authors (2023)

Table 2. Unconditional correlation matrix

	OIL_BRENT	GOLD	ZAR	MAD	KES	NGN	MUR	NAD	JSE	CSE	KSE	NGX	MSE	NSE	RSA_10YR	MOR_10YR	KEN_10YR	NIG_10YR	MAU_10YR	NAM_10YR
OIL_BRENT	1																			
GOLD	0.07	1																		
ZAR	−0.04	−0.09	1																	
MAD	−0.13	−0.11	0.25	1																
KES	0.02	0.07	−0.06	0.09	1															
NGN	0.01	0.04	−0.07	−0.01	0.01	1														
MUR	−0.12	0.04	−0.03	−0.01	0.00	−0.06	1													
NAD	−0.07	−0.08	0.94	0.26	−0.05	−0.01	−0.03	1												
JSE	−0.15	0.06	−0.05	0.01	0.04	0.05	0.02	−0.03	1											
CSE	0.03	−0.03	−0.01	−0.01	−0.06	−0.05	−0.02	0.00	−0.04	1										
KSE	0.02	−0.03	−0.13	−0.07	0.06	−0.06	0.01	−0.13	0.10	0.18	1									
NGX	0.12	0.05	−0.01	−0.01	−0.04	0.01	−0.02	0.00	0.07	0.17	0.00	1								
MSE	−0.02	0.05	0.07	0.06	−0.03	0.01	0.01	0.06	0.07	0.07	−0.07	0.09	1							
NSE	0.02	−0.02	0.04	0.02	−0.01	0.00	−0.02	0.04	0.08	0.03	−0.02	−0.07	0.06	1						
RSA_10YR	0.03	0.03	−0.04	0.06	−0.06	0.02	−0.03	−0.04	−0.04	−0.05	−0.01	0.00	−0.03	0.00	1					
MOR_10YR	0.02	−0.02	0.00	0.02	0.00	0.00	−0.03	−0.02	−0.01	0.00	−0.01	0.02	−0.03	0.00	−0.05	1				
KEN_10YR	−0.08	0.03	0.01	−0.01	−0.01	−0.03	−0.06	0.00	0.04	0.01	0.00	−0.02	0.04	0.00	−0.04	0.05	1			
NIG_10YR	−0.01	−0.05	−0.01	0.04	−0.01	0.01	−0.01	0.00	0.05	−0.02	0.01	0.02	0.01	0.02	−0.02	0.06	−0.08	1		
MAU_10YR	0.00	0.02	0.01	−0.02	0.00	0.01	−0.01	0.00	−0.03	−0.02	−0.04	−0.05	0.00	0.00	0.04	0.00	0.00	−0.03	1	
NAM_10YR	0.00	0.06	−0.01	−0.03	0.02	−0.01	−0.03	−0.01	0.00	−0.01	−0.06	−0.03	−0.05	0.02	0.02	−0.08	0.01	0.03	0.01	1

Source(s): Table by authors (2023)

Table 3. Static return connectedness of all assets

	OIL_ BRENT	GOLD	ZAR	MAD	KES	NGN	MUR	NAD	JSE	CSE	KSE	NGX	MSE	NSE	RSA_ 10YR	MOR_ 10YR	KEN_ 10YR	NIG_ 10YR	MAU_ 10YR	NAM_ 10YR	From others
OIL_BRENT	70.9	1	2	3.9	2.8	0.8	2.5	1.7	3.3	2.5	0.5	1.3	3.3	0.4	0.5	0.1	1.1	0.6	0.3	0.3	29.1
GOLD	1.3	76.8	1.8	1.4	1.2	5.2	0.3	1.9	1	0.7	1.2	0.3	0.5	0.7	1.2	1.5	1.9	0.4	0.4	0.4	23.2
ZAR	0.5	0.7	45.5	3.9	0.4	0.6	0.6	41.7	0.7	0.3	1.3	0.4	1	0.4	0.3	0.5	0.4	0.7	0.1	0.2	54.5
MAD	2.5	1	5.3	75.2	1.5	0.5	0.6	5.4	0.8	0.3	2.1	0.1	1.7	0.5	0.5	0.1	0.3	0.7	0.3	0.5	24.8
KES	0.4	0.3	1.2	1.2	83	3.9	0.9	1.2	0.4	1.6	0.6	0.7	1	0.1	1	0.3	0.1	0.2	0.6	0.8	16.6
NGN	0.7	3.2	1.2	2.9	0.8	84.5	1	1	0.5	1.3	0.4	0.5	0.2	0.1	0.5	0.4	0.4	0.1	0.2	0.1	15.5
MUR	1.8	0.9	0.3	1.3	0.2	2.8	87.6	0.1	0.4	0.2	0.1	0.7	0.2	0.1	0.1	0.6	1.1	0.3	0.3	0.9	12.4
NAD	0.9	0.9	42.3	3.6	0.6	0.6	0.3	45.4	0.6	0.3	1.1	0.3	0.7	0.5	0.3	0.5	0.3	0.6	0.1	0.1	54.6
JSE	3	1.9	0.5	1.3	0.3	0.5	0.4	0.4	73.2	9.4	2	0.9	3.2	0.7	0.7	0.2	0.2	0.9	0.2	0.2	26.8
CSE	3.1	0.9	0.9	2.1	1.4	0.8	0.2	0.9	4.1	69.7	2.5	4.9	6.4	0.2	0.3	1.1	0.1	0.1	0.3	0.1	30.3
KSE	0.4	0.5	3.9	2.8	1.7	0.4	0.2	3.5	1.6	1.8	74.9	1.5	4.4	0.2	0.2	0.2	0.2	0.5	0.3	0.8	25.1
NGX	2	0.5	0.2	0.6	3	0.5	0.6	0.1	1.9	0.9	0.2	81.3	1	1.2	0.8	0.9	1.9	0.2	0.5	1.7	18.7
MSE	2.2	1.3	1.4	1.7	1.6	0.1	0.3	1	6.4	3.8	1.3	1.6	74.6	0.3	0.2	0.5	0.6	0.1	0.1	0.6	25.4
NSE	1.2	0.4	0.7	0.2	0	0	0.1	0.7	1.6	0.3	0.6	1.2	0.3	91.9	0.3	0	0.1	0	0	0.3	8.1
RSA_10YR	0.4	0.9	0.4	0.5	1.7	0.6	0.7	0.4	0.5	0.1	0.2	1.1	0.4	0.2	89.6	0.2	0.5	0.6	0.4	0.9	10.4
MOR_10YR	0.3	0.2	0.3	0.5	0.1	0	0.2	0.3	0.4	0.3	0.7	0.9	0.5	0	0.3	92.2	0.4	0.8	0.1	1.5	7.8
KEN_10YR	3.1	0.4	0.3	1.3	0.5	1.5	0.7	0.1	0.3	0.5	0.1	1.4	0.2	0.9	0.5	0.4	85.9	0.9	0.3	0.6	14.1
NIG_10YR	0.2	0.3	0.7	0.6	0.3	0	0.6	0.6	0.6	0.5	0.7	0.1	0.3	0.1	0.7	0.6	0.5	90.7	0.2	1.5	9.3
MAU_10YR	0.1	0.7	1.7	0.2	0.4	0.2	0.2	1.9	0.4	0.2	0.4	0.7	0.1	0.1	0.9	0.2	0.8	0.2	89.7	1.3	10.3
NAM_10YR	0.2	0.3	0.2	0.7	0.4	0.3	0.5	0.3	0.3	0.1	0.8	1.4	0.7	0.2	0.6	2.4	0.5	2.7	0.6	86.9	13.1
TO OTHERS	24.2	16.2	65.2	30.8	19	19.4	10.9	63.4	25.8	24.9	16.9	19.9	26.1	6.9	9.8	10.7	11.5	10.7	5.2	12.7	21.50%
NET	−4.9	−7	10.7	6	2.4	3.9	−1.5	8.8	−1	−5.4	−8.2	1.2	0.7	−1.2	−0.6	2.9	−2.6	1.4	−5.1	−0.4	
CONCLUSION	NR	NR	NT	NT	NT	NT	NR	NT	NR	NR	NR	NT	NT	NR	NR	NT	NR	NT	NR	NR	

Source(s): Table by authors (2023)

We also observe inter-market pairwise connectedness. The pairwise connectedness from the Kenyan stock market to the Moroccan dirham is 2.1%, while the pairwise connectedness from the South African rand to the Mauritius bond market is 1.7%.

5.2 Time-varying (dynamic) connectedness

Figure 2 presents the time-varying connectedness plot. One of the main shortcomings of the static connectedness measure, in Table 3, is the assumption of constant connectedness over time. The static connectedness table may ignore the asset return fluctuations or jumps that are mostly associated with financial or economic crises. To overcome this setback, Figure 2 analyzes the time-varying return connectedness using a 120-day rolling sample window, 10-day prediction horizon and the VAR model lag order, $p = 3$, in the forecast error variance decomposition. The figure shows that the total connectedness graph fluctuated between 51.50% and 69.80% during the pandemic. During the peak of the first wave of the pandemic, the return connectedness was 68.35% on April 2, 2020. The return connectedness index fluctuated and reached a minimum of 51.50% on February 2, 2021. The index started rising in February 2021, the tail end of the second wave of the pandemic, to 62% on June 11, 2021. Overall, the dynamic (time-varying) connectedness plot exhibits a downward trend during the first wave of the pandemic and an upward trend during the second wave. This shows evidence of dynamic time-varying connectedness and implies time-varying diversification opportunities.

Table 4 shows the net-pairwise directional spillovers obtained from Table 3. The "Net" row is the net-total connectedness between an asset and all other assets. For example, the South African stock market transmitted 23.9% of its shocks to others but received 25.3% from others. South Africa is a net receiver (−1.4%) from all other markets or assets. South Africa and Morocco were the two most affected countries as of November 18, 2022, with 4,036,623 and 1,146,799) cases, respectively. The South African stock market is a net receiver (−5.1%) of return shocks, whereas Morocco is a net transmitter (5.1%). Surprisingly, both oil (−5.6%) and gold (−6.5%) are net receivers of shocks. Our findings are consistent with what Morema and Bonga-Bonga (2020) found in South Africa and Lahiani *et al.* (2021) found in the US.

On the contrary, Mensi *et al.* (2020) found gold and oil as net transmitters of shocks, but Liao *et al.* (2021) found gold as a net receiver and as a net transmitter of shocks. Our findings indicate that both oil and gold can be used to hedge against the risk of an investment portfolio containing forex, stocks and bonds in Africa. The entries in the body of the table are the net-pairwise connectedness between two assets. The highest pairwise connectedness, 9.1%, is obtained from Morocco to the South African stock market. In return, the pairwise connectedness from South Africa to the Morocco stock market is 4.0%. The difference, 5.1%, is the net-pairwise connectedness. The positive value indicates that Morocco is a net transmitter between the two markets, and South Africa is a net receiver of shocks.

5.3 Network connectedness

We present a full sample net pairwise connectedness (network) plot in Figure 3. The network graph allows us to visualize the strengths in the net pairwise connectedness. In the full sample, we use a circular layout function for net pairwise network connectedness. This algorithm shows the distribution of the nodes (assets) with their links (edges). It draws nodes in an ordered circular form. We use another statistical algorithm, Modularity class, to cluster the nodes (assets) in the network into communities using color. Nodes of the same color indicate the strength of the connections. We noticed that most nodes are pink, and the rest are green. Nodes having the same color means they have similar attributes or characteristics. The node size also shows the magnitude of the net total directional spillovers in real value terms.

Table 4. Net pairwise return connectedness of all assets

	OIL_ BRENT	GOLD	ZAR	MAD	KES	NGN	MUR	NAD	JSE	CSE	KSE	NGX	MSE	NSE	RSA_ 10YR	MOR_ 10YR	KEN_ 10YR	NIG_ 10YR	MAU_ 10YR	NAM_ 10YR
OIL_ BRENT	0	−0.3	1.5	1.4	2.4	0.1	0.7	0.8	0.3	−0.6	0.1	−0.7	1.1	−0.8	0.1	−0.2	−2	0.4	0.1	0.1
GOLD	0.3	0	1.1	0.4	0.9	2	−0.6	−1	−0.9	−0.2	0.7	−0.2	−0.8	0.3	0.3	1.3	1.5	0.1	−0.3	0.1
ZAR	−1.5	−1.1	0	−1.4	−0.8	−0.6	0.3	−0.6	0.2	−0.6	−2.6	0.2	−0.4	−0.3	−0.1	0.2	0.1	0	−1.6	0
MAD	−1.4	−0.4	1.4	0	0.3	−2.4	−0.7	1.8	−0.5	−1.8	−0.7	−0.5	0	0.3	0	−0.4	−1	0.1	0.1	−0.2
KES	−2.4	−0.9	0.8	−0.3	0	3.1	0.7	0.6	0.1	0.2	−1.1	−2.3	−0.6	0.1	−0.7	0.2	−0.4	−0.1	0.2	0.4
NGN	−0.1	−2	0.6	2.4	−3.1	0	−1.8	0.4	0	0.5	0	0	0.1	0.1	−0.1	0.4	−1.1	−0.1	0	−0.2
MUR	−0.7	0.6	−0.3	0.7	−0.7	1.8	0	−0.2	0	0	−0.1	0.1	−0.1	0	−0.6	0.4	0.4	−0.3	0.1	0.4
NAD	−0.8	−1	0.6	−1.8	−0.6	−0.4	0.2	0	0.2	−0.6	−2.4	0.2	−0.3	−0.2	−0.1	0.2	0.2	0	−1.8	−0.2
JSE	−0.3	0.9	−0.2	0.5	−0.1	0	0	−0.2	0	5.3	0.4	−1	−3.2	−0.9	0.2	−0.2	−0.1	0.3	−0.2	−0.1
CSE	0.6	0.2	0.6	1.8	−0.2	−0.5	0	0.6	−5.3	0	0.7	4	2.6	−0.1	0.2	0.8	−0.4	0.2	0.1	0
KSE	−0.1	−0.7	2.6	0.7	1.1	0	0.1	2.4	−0.4	−0.7	0	1.3	−3.1	−0.4	0	−0.5	0.1	−0.2	−0.1	0
NGX	0.7	0.2	−0.2	0.5	2.3	0	−0.1	−0.2	1	−4	−1.3	0	−0.6	0	−0.3	0	0.5	0.1	−0.2	0.3
MSE	−1.1	0.8	0.4	0	0.6	−0.1	0.1	0.3	3.2	−2.6	3.1	0.6	0	0	−0.2	0	0.4	−0.2	0	−0.1
NSE	0.8	−0.3	0.3	−0.3	−0.1	−0.1	0	0.2	0.9	0.1	0.4	0	0	0	0.1	0	−0.8	−0.1	−0.1	0.1
RSA_ 10YR	−0.1	−0.3	0.1	0	0.7	0.1	0.6	0.1	−0.2	−0.2	0	0.3	0.2	−0.1	0	−0.1	0	−0.1	−0.5	0.3
MOR_ 10YR	0.2	−1.3	−0.2	0.4	−0.2	−0.4	−0.4	−0.2	0.2	−0.8	0.5	0	0	0	0.1	0	0	0.2	−0.1	−0.9
KEN_ 10YR	2	−1.5	−0.1	1	0.4	1.1	−0.4	−0.2	0.1	0.4	−0.1	−0.5	−0.4	0.8	0	0	0	0.4	−0.5	0.1
NIG_ 10YR	−0.4	−0.1	0	−0.1	0.1	−0.1	0.3	0	−0.3	−0.2	0.2	−0.1	0.2	0.1	0.1	−0.2	−0.4	0	0	−1.2
MAU_ 10YR	−0.1	0.3	1.6	−0.1	−0.2	0	−0.1	1.8	0.2	−0.1	0.1	0.2	0	0.1	0.5	0.1	0.5	0	0	0.7
NAM_ 10YR	−0.1	−0.1	0	0.2	−0.4	0.2	−0.4	0.2	0.1	0	0	−0.3	0.1	−0.1	−0.3	0.9	−0.1	1.2	−0.7	0

Source(s): Table by authors (2023)

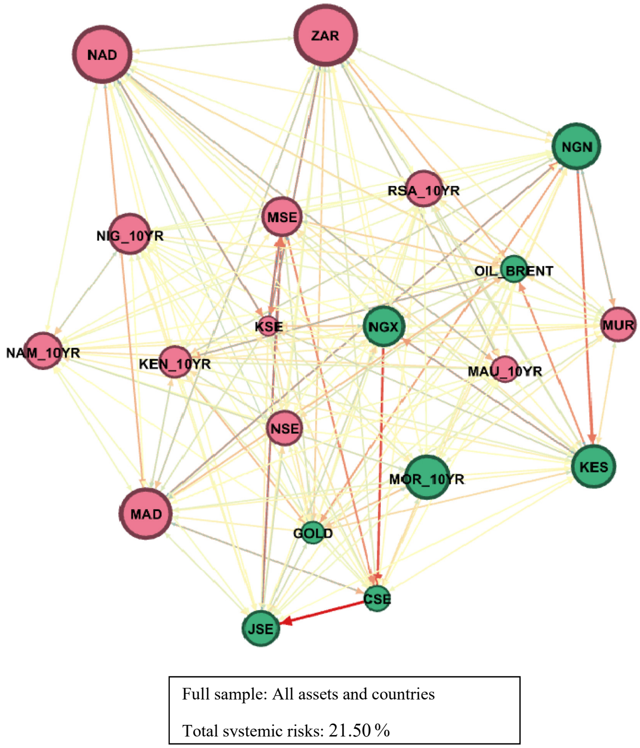
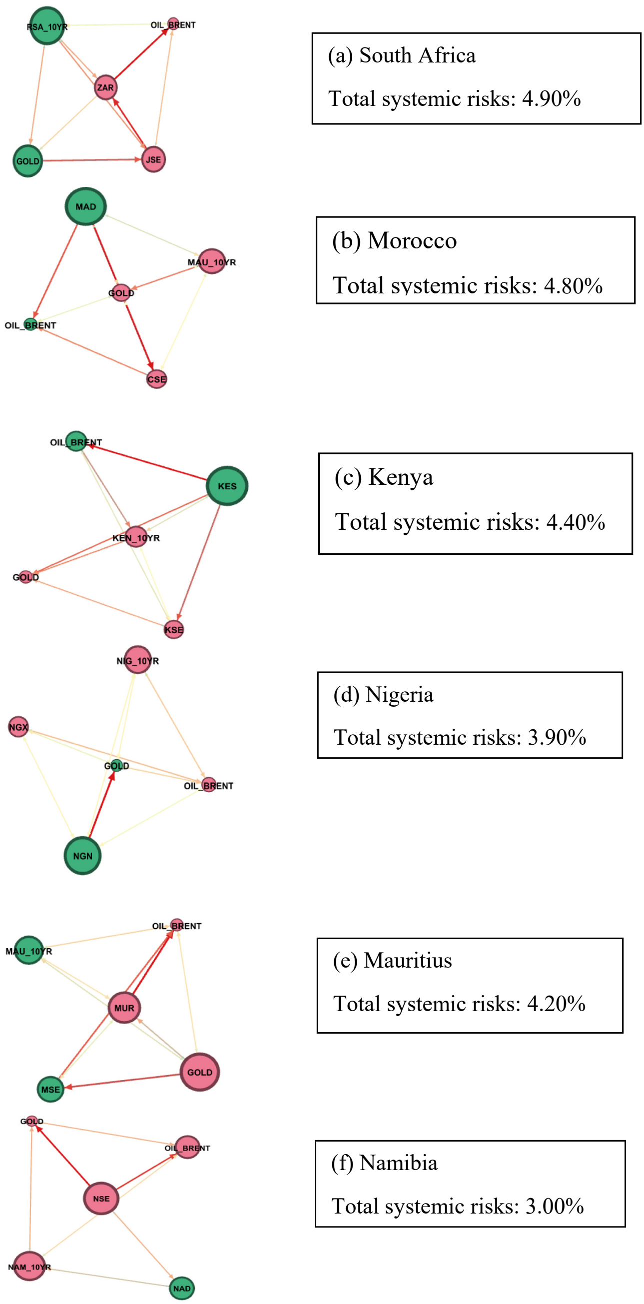


Figure 3.
Net pairwise network connectedness across all countries and assets

Source(s): Figure by authors (2023)

The color of the edge shows the strength of the net-pairwise connectedness between the two assets, and the arrow direction indicates the direction of the spillover. For instance, the results show that the South African stock market is a net receiver, while the Moroccan stock market is a net transmitter of return shocks.

We also perform the net pairwise network connectedness of the various assets in each country in Figure 4. In this analysis, we use a layout function called Force Atlas 2. This algorithm pulls strongly connected nodes together in the middle of the network and pushes weakly connected node(s) apart. We found high systemic risks in South Africa (4.90%) and low in Namibia (3.00%). In South Africa, the most connected asset is the rand, which sits at the network's center. Return shock spillover runs from the stock market to the forex market. Equities and forex are strongly connected assets. A study by Morema and Bonga-Bonga (2020) found a negative correlation between stock and gold markets during the global financial crisis in South Africa. We distinguish between gold and equity as net transmitters or receivers of shocks. We found that gold is a net transmitter while the stock market is a net receiver of shocks in South Africa. In Morocco, the forex market and the stock market are highly connected. However, the forex market is a net transmitter (2.3%) of shocks, while the stock market is a net receiver (−2.3%). In Nigeria, we found that the naira and gold are highly connected. However, return shock spillovers run from the naira to gold. In Kenya and Mauritius, the forex and crude oil are highly connected with return shocks running from the forex market to crude oil. In Namibia, the stock market and gold, and also the stock market and crude oil, have similar strengths in their connectedness.



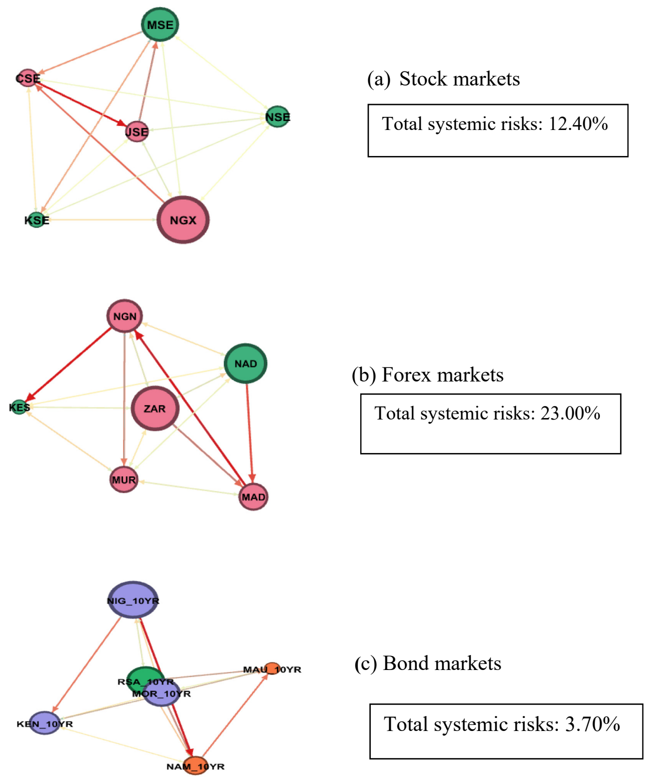
Source(s): Figure by authors (2023)

Figure 4.
Country-level net pairwise directional network connectedness

In the intra-market analysis, we found higher systemic risks in the forex markets (23.00%) than in the stock markets (12.40%) and the bonds (3.70%) as shown in Figure 5. This shows that the COVID-19-induced financial crisis emanating from the US stock market has negative consequences in the African currencies than the stock and bond markets. In the forex market, there is equal strength in the net pairwise connectedness of 4.1% between the Nigerian naira and the Kenyan shilling and that of the Moroccan dirham and the Nigerian naira. The South African rand sits at the center of the network, indicating that the rand is more connected to other currencies during the pandemic. In the stock market, again, we notice that the South African stock market is found at the center of the network, indicating that the South African stock market is more connected to other stock markets. In the bond markets, we observe that the South African and the Moroccan bond markets are tightly connected in the African bond markets network.

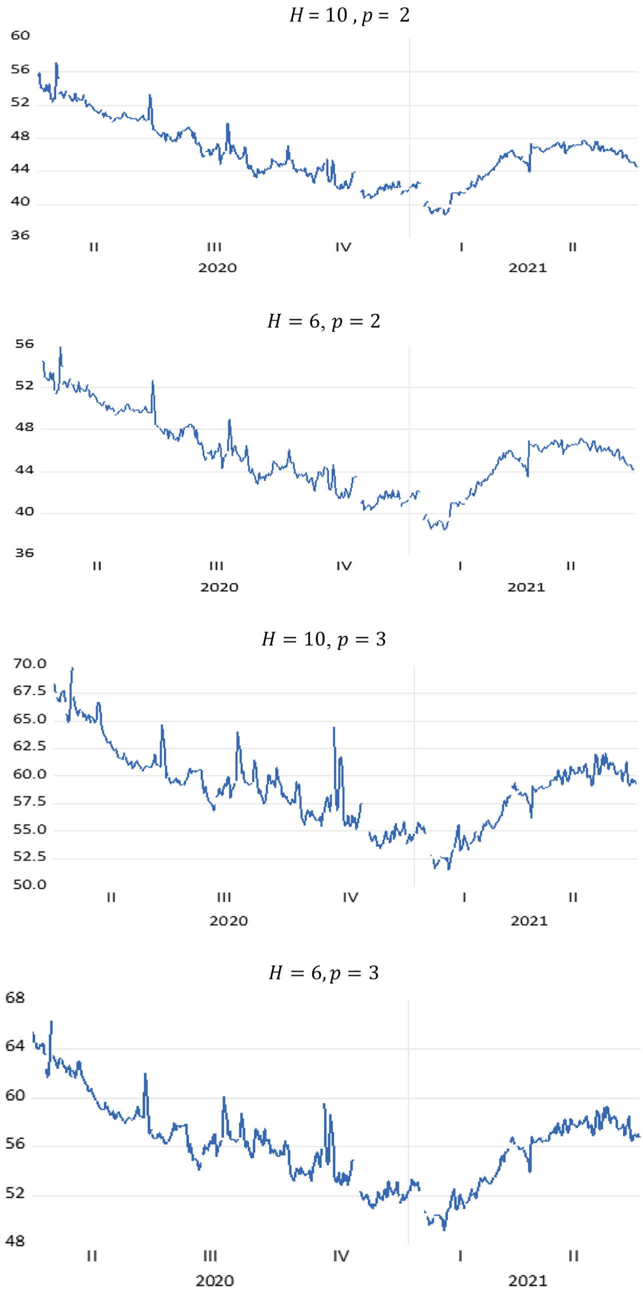
5.4 Robustness test

We follow Wen *et al.* (2020), Yoon *et al.* (2019), Diebold and Yilmaz (2014, 2016), and Antonakakis (2012) in our robustness analysis as shown in Figure 6. Using different forecast horizons and VAR lag lengths, we check the sensitivity of the H-step-ahead forecast-error variance decomposition of the return connectedness plot of Figure 2. We do so by varying the forecast horizon, H, and the VAR model order, *p*. We observed that the total return



Source(s): Figure by authors (2023)

Figure 5.
Market-level net pairwise directional network connectedness



Source(s): Figure by authors (2023)

Figure 6.
Robustness to forecast horizon and VAR lag length of the total return dynamic connectedness across assets and countries

connectedness plots are robust to changes in the forecast horizon of $H = 6$ and $p = 2$ to $H = 10$ and $p = 2$, and also $H = 6$ and $p = 3$ to $H = 10$ days and $p = 3$. This means that the choice of forecast horizon and the VAR order do not influence the time-varying connectedness.

6. Conclusion and policy implications

This study estimates the magnitude of the systemic risks and the net total and pairwise directional return shock spillovers across commodities (oil, gold) and African financial markets (forex, stocks, bonds) during the Covid-19 pandemic. We employed Diebold and Yilmaz (2012, 2014, 2016) spillover and connectedness measures to estimate the total systemic risks and the net directional spillovers, and perform the dynamic rolling window analysis of all the assets and countries. We also use a network visualization tool, Gephi, to visualize the strength of net pairwise connectedness.

We summarize our findings as follows. First, we found low total systemic risks across all markets and countries. However, we found higher systemic risks in the forex markets than in the stock and bond markets. The country-level analysis found high systemic risks in South Africa and low in Namibia. The low total systemic risks imply relatively weak interdependence or return shock transmission between different markets. In other words, there is a limited spillover of return shocks from one market to the others. Thus, there is a good diversification opportunity for African financial assets. We also found the time-varying connectedness that increased during the peak periods of the first and second waves of the pandemic, which indicates time-varying diversification opportunities for Africa's financial assets. Again, we found that nine assets are net transmitters, while eleven are net receivers of return shocks. The South African rand is the highest transmitter of return shocks to all other assets. At the same time, the Namibian dollar was the greatest recipient of shocks from all other assets. Both gold and oil are net receivers of shocks from all other assets. This means that gold and oil could not provide the needed diversification benefits during the pandemic due to their sensitivity or vulnerability to shocks from other financial assets. Furthermore, the network connectedness plot shows a higher net pairwise connectedness from Morocco to the South African stock markets followed by from Nigeria and Morocco stock markets.

The study has important implications for investors, portfolio managers and policymakers. The findings indicate that portfolio managers and investors should bear in mind the increased market connectedness during crisis periods so as to design strategies to achieve higher diversification benefits. Portfolio managers can also use the nature of return volatility spillovers to know whether a particular country or asset is a net shock receiver or transmitter for enhanced portfolio hedging strategies. After all, giving out shocks is better than receiving them (Diebold and Yilmaz, 2012). From a policy perspective, African governments should deliberately develop the capacity of local investors and markets to reduce capital outflows during crises. It is evident from the country-level analysis that Namibia, which has a well-developed local pensions market, recorded low systemic risks during the pandemic.

References

Abuzayed, B. and Al-Fayoumi, N. (2021), "Risk spillover from crude oil prices to GCC stock market returns: new evidence during the COVID-19 outbreak", *North American Journal of Economics and Finance*, Vol. 58, 101476, doi: 10.1016/j.najef.2021.101476.

Acharya, V., Pedersen, L., Philippe, T. and Richardson, M. (2010), *Measuring Systemic Risk*, Manuscript, Stern School, New York University.

Acharya, V., Engle, R. and Richardson, M. (2012), "Capital shortfall: a new approach to ranking and regulating systemic risks", *American Economic Review*, Vol. 102 No. 3, pp. 59-64, doi: 10.1257/aer.102.3.59.

Adrian, T. and Brunnermeier, M.K. (2001), "CoVaR", NBER Working Paper No. 17454.

African Development Bank (2021), "Africa economic outlook report".

African Financial Market Index (2020), "Africa's possibility is in the detail. Official monetary and financial institutions forum", 4th ed., available at: www.omfif.org

Akhtaruzzaman, M., Benkraiem, R., Boubaker, S. and Zopounidis, C. (2022), "COVID-19 crisis and risk spillovers to developing economies: evidence from Africa", *Journal of International Development*, Vol. 34 No. 4, pp. 898-918, doi: 10.1002/jid.3634.

Antonakakis, N. (2012), "Exchange return co-movements and volatility spillovers before and after the introduction of euro", *Journal of International Financial Markets, Institutions and Money*, Vol. 22 No. 5, pp. 1091-1109.

Antonakakis, N., Chatziantoniou, I. and Gabauer, D. (2020), "Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions", *Journal of Risk and Financial Management*, Vol. 13 No. 4, p. 84.

Arfaoui, M. and Ben Rejeb, A. (2017), "Oil, gold, US dollar and stock market interdependencies: a global analytical insight", *European Journal of Management and Business Economics*, Vol. 26 No. 3, pp. 278-293, doi: 10.1108/ejmbe-10-2017-016.

Atenga, E.M.E. and Mougoué, M. (2021a), "Return and volatility spillovers to African equity markets and their determinants", *Empirical Economics*, Vol. 61 No. 2, pp. 883-918, doi: 10.1007/s00181-020-01881-9.

Atenga, E.M.E. and Mougoué, M. (2021b), "Return and volatility spillovers to African currencies markets", *Journal of International Financial Markets, Institutions and Money*, Vol. 73, 101348, doi: 10.1016/j.intfin.2021.101348.

Awartani, B. and Maghyereh, A.I. (2013), "Dynamic spillovers between oil and stock markets in the gulf cooperation council countries", *Energy Economics*, Vol. 36, pp. 28-42, doi: 10.1016/j.eneco.2012.11.024.

Baele, L., Bekaert, G., Ingelbrecth, K. and Wei, M. (2020), "Flights to safety", *Review Financial Studies*, Vol. 33 No. 2, pp. 689-746, doi: 10.1093/rfs/hhz055.

Bagchi, B. (2017), "Volatility spillovers between crude oil price and stock markets: evidence from BRIC countries", *International Journal of Emerging Markets*, Vol. 12 No. 2, pp. 352-365, doi: 10.1108/ijoem-04-2015-0077.

Bagheri, E. and Ebrahimi, S.B. (2020), "Estimating network connectedness of financial markets and commodities", *Journal of Systems Science and Systems Engineering*, Vol. 29 No. 5, pp. 572-589, doi: 10.1007/s11518-020-5465-1.

Bakas, D. and Triantafyllou, A. (2020), "Commodity price volatility and the economic uncertainty of pandemics", *Economics Letters*, Vol. 193, 109283, doi: 10.1016/j.econlet.2020.109283.

Baker, S.R., Bloom, N., Davis, S.J., Kost, K.J., Sammon, M.C. and Viratyosin, T. (2020), "The unprecedented stock market impact of Covid-19", NBER Working Papers Series.

Baruník, J. and Křehlík, T. (2018), "Measuring the frequency dynamics of financial connectedness and systemic risk", *Journal of Financial Econometrics*, Vol. 16 No. 2, pp. 271-296, doi: 10.1093/jjfinec/nby001.

Baruník, J., Kočenda, E. and Vácha, L. (2017), "Asymmetric volatility connectedness on the forex market", *Journal of International Money and Finance*, Vol. 77, pp. 39-56, doi: 10.1016/j.jimonfin.2017.06.003.

Beckmann, J. and Czudaj, R. (2013), "Oil and gold price dynamics in a multivariate cointegration framework", *International Economics and Economic Policy*, Vol. 10 No. 3, pp. 453-468, doi: 10.1007/s10368-013-0237-8.

Billio, M., Donadelli, M., Paradiso, A. and Riedel, M. (2017), "Which market integration measure?", *Journal of Banking and Finance*, Vol. 76, pp. 150-174.

Boako, G. and 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*, Vol. 468, pp. 359-380, doi: 10.1016/j.physa.2016.10.088.

Boako, G. and Alagidede, P. (2018), "Systemic risks spillovers and interdependence among stock markets: international evidence with CoVaR-copulas", *South African Journal of Economics*, Vol. 86 No. 1, pp. 82-112, doi: 10.1111/saje.12182.

Boakye, R.O., Mensah, L.K., Kang, S.H. and Osei, K.A. (2023), "Foreign exchange market return spillovers and connectedness among African countries", *International Review of Financial Analysis*, Vol. 86, 102505, doi: 10.1016/j.irfa.2023.102505.

Bouri, E., Cepni, O., Gabauer, D. and Gupta, R. (2021), "Return connectedness across asset classes around the COVID-19 outbreak", *International Review of Financial Analysis*, Vol. 73, 101646, doi: 10.1016/j.irfa.2020.101646.

Carsamer, E. (2016), "The pattern of exchange rate co-movement in selected African countries", *Journal of Economic Studies*, Vol. 43 No. 6, pp. 928-953, doi: 10.1108/jes-05-2015-0074.

Diebold, F.X. and Yilmaz, K. (2012), "Better to give than to receive: predictive directional measurement of volatility spillovers", *International Journal of Forecasting*, Vol. 28 No. 1, pp. 57-66, doi: 10.1016/j.ijforecast.2011.02.006.

Diebold, F.X. and Yilmaz, K. (2014), "On the network topology of variance decompositions: measuring the connectedness of financial firms", *Journal of Econometrics*, Vol. 182 No. 1, pp. 119-134, doi: 10.1016/j.jeconom.2014.04.012.

Diebold, F.X. and Yilmaz, K. (2015), *Financial and Macroeconomics Connectedness: A Network Approach to Measurement and Monitoring*, Oxford University Press, USA.

Diebold, F.X. and Yilmaz, K. (2016), "Trans-Atlantic equity volatility connectedness: US and European financial institutions, 2004-2014", *Journal of Financial Econometrics*, Vol. 14 No. 1, pp. 81-127.

Duncan, A.S. and Kabundi, A. (2013), "Domestic and foreign sources of volatility spillover to South African asset classes", *Economic Modelling*, Vol. 31 No. 1, pp. 566-573, doi: 10.1016/j.econmod.2012.11.016.

Edwards, S. and Susmel, R. (2001), "Volatility dependence and contagion in emerging equity markets", *Journal of Development Economics*, Vol. 66 No. 2, pp. 505-532, doi: 10.1016/s0304-3878(01)00172-9.

Engle, R. (2009), *Anticipating Correlations: A New Paradigm for Risk Management*, Princeton University Press, Princeton, NJ.

Engle, R. and Kelly, B. (2012), "Dynamic equicorrelation", *Journal of Business and Economic Statistics*, Vol. 30 No. 2, pp. 212-228, doi: 10.1080/07350015.2011.652048.

Farid, S., Kayani, G.M., Naeem, M.A. and Shahzad, S.J.H. (2021), "Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic", *Resources Policy*, Vol. 72, 102101, doi: 10.1016/j.resourpol.2021.102101.

Fasanya, I. and Oyewole, O. (2023), "On the connection between clean energy stocks and African stock markets: does uncertainty due to infectious diseases matter?", *International Journal of Emerging Markets*. doi: 10.1108/ijoem-05-2022-0818.

Gao, J., Hou, Y., Fan, F. and Liu, F. (2020), "Complexity changes in the US and China's stock markets: differences, causes, and wider social implications", *Entropy*, Vol. 22 No. 1, p. 75.

Gourène, G.A.Z., Mendy, P. and Ake, G.M.N.G. (2019a), "Multiple time-scales analysis of global stock markets spillover effects in African stock markets", *International Economics*, Vol. 157, pp. 82-98, doi: 10.1016/j.inteco.2018.09.001.

Gourène, G.A.Z., Mendy, P. and Diomande, L. (2019b), "Beginning an african stock markets integration? A wavelet analysis", *Journal of Economic Integration*, Vol. 34 No. 2, pp. 370-394, doi: 10.11130/jei.2019.34.2.370.

Hamao, Y., Masulis, R.W. and Ng, V. (1990), "Correlations in price changes and volatility across international stock markets", *Review of Financial Studies*, Vol. 3 No. 2, pp. 281-307, doi: 10.1093/rfs/3.2.281.

Jeribi, A. and Ghorbel, A. (2021), "Forecasting developed and BRICS stock markets with cryptocurrencies and gold: generalized orthogonal generalized autoregressive conditional heteroskedasticity and generalized autoregressive score analysis", *International Journal of Emerging Markets*, Vol. 17 No. 9, pp. 2290-2320, doi: 10.1108/ijoem-06-2020-0688.

Kang, S.H. and Lee, J.W. (2019), "The network connectedness of volatility spillovers across global futures markets", *Physica A: Statistical Mechanics and Its Applications*, Vol. 526, 120756, doi: 10.1016/j.physa.2019.03.121.

King, M.A. and Wadhwani, S. (1990), "Transmission of volatility between stock markets", *Review of Financial Studies*, Vol. 3 No. 1, pp. 5-33, doi: 10.1093/rfs/3.1.5.

Khalfaoui, R., Boutahar, M. and Boubaker, H. (2015), "Analyzing volatility spillovers and hedging between oil and stock markets: evidence from wavelet analysis", *Energy Economics*, Vol. 49, pp. 540-549.

King, M., Sentana, E. and Wadhwani, S. (1994), "Volatility and links between national stock markets", *Journal of the Econometric Society*, Vol. 62 No. 4, pp. 901-933, doi: 10.2307/2951737.

Koop, G.M., Pesaran, M.H. and Potter, S.M. (1996), "Impulse response analysis in nonlinear multivariate models", *Journal of Econometrics*, Vol. 74 No. 1, pp. 119-147, doi: 10.1016/0304-4076(95)01753-4.

Lahiani, A. and Jlassi, N.B. (2021), "Nonlinear tail dependence in cryptocurrency-stock market returns: the role of bitcoin futures", *Research in International Business and Finance*, Vol. 56, 101351.

Lahiani, A., Mefteh-Wali, S. and Vasbieva, D.G. (2021), "The safe-haven property of precious metal commodities in the COVID-19 era", *Resources Policy*, Vol. 74, 102340.

Liao, J., Zhu, X. and Chen, J. (2021), "Dynamic spillovers across oil, gold and stock markets in the presence of major public health emergencies", *International Review of Financial Analysis*, Vol. 77, 101822, doi: 10.1016/j.irfa.2021.101822.

Lin, W.-L., Engle, R.F., Ito, T. and Ito, N.T. (1991), "Do bulls and bears move across borders? International transmission of stock returns and volatility as the world turns", *Review of Financial Studies*, Vol. 7 No. 3, pp. 507-538, doi: 10.1093/rfs/7.3.507.

Longin, F. and Solnik, B. (2001), "Extreme correlation of international equity markets", *Journal of Finance*, Vol. 56 No. 2, pp. 649-676, doi: 10.1111/0022-1082.00340.

Marobhe, M.I. (2022), "Cryptocurrency as a safe haven for investment portfolios amid COVID-19 panic cases of Bitcoin, Ethereum and Litecoin", *China Finance Review International*, Vol. 12 No. 1, pp. 51-68, doi: 10.1108/cfri-09-2021-0187.

Mensi, W., Rehman, M.U. and Vo, X.V. (2020), "Spillovers and co-movements between precious metals and energy markets: implications on portfolio management", *Resources Policy*, Vol. 69, 101836, doi: 10.1016/j.resourpol.2020.101836.

Mensi, W., Al-Yahyaee, K.H., Vo, X.V. and Kang, S.H. (2021), "Modelling the frequency dynamics of spillovers and connectedness between crude oil and MENA stock markets with portfolio implications", *Economic Analysis and Policy*, Vol. 71, pp. 397-419, doi: 10.1016/j.eap.2021.06.001.

Mezghani, T. and Boujelbène-Abbes, M. (2021), "Financial stress effects on financial markets: dynamic connectedness and portfolio hedging", *International Journal of Emerging Markets*, Vol. 18 No. 10, pp. 4064-4087, doi: 10.1108/ijoem-06-2020-0619.

Morema, K. and Bonga-Bonga, L. (2020), "The impact of oil and gold price fluctuations on the South African equity market: volatility spillovers and financial policy implications", *Resources Policy*, Vol. 68, 101740, doi: 10.1016/j.resourpol.2020.101740.

Newman, M.E.J. (2010), *Networks: an Introduction*, Oxford University Press, Oxford.

Owusu Junior, P., Adam, A.M. and Tweneboah, G. (2017), "Co-Movement of real exchange rates in the west african monetary zone", *Cogent Economics and Finance*, Vol. 5 No. 1, 1351807, doi: 10.1080/23322039.2017.1351807.

Pesaran, M.H. and Shin, Y. (1998), "Generalized impulse response analysis in linear multivariate models", *Economics Letters*, Vol. 58 No. 1, pp. 17-29, doi: 10.1016/s0165-1765(97)00214-0.

Polat, O. (2022), "On systemic risk contagion in the euro area: evidence from frequency connectedness and the DY approaches", *Borsa Istanbul Review*, Vol. 22 No. 3, pp. 441-451, doi: 10.1016/j.bir.2021.06.011.

Pukthuanthong, K. and Roll, R. (2009), "Global market integration: an alternative measure and its applications", *Journal of Financial Economics*, Vol. 94 No. 2, pp. 214-232, doi: 10.1016/j.jfineco.2008.12.004.

Ragunathan, V. (1999), "Financial deregulation and integration: an Australian perspective", *Journal of Economics and Business*, Vol. 51 No. 6, pp. 505-514, doi: 10.1016/s0148-6195(99)00018-1.

Roll, R. (1989), Price volatility, international market Links, and their implications for.

Rubbaniy, G., Khalid, A.A., Syriopoulos, K. and Samitas, A. (2022), "Safe-haven properties of soft commodities during times of COVID-19", *Journal of Commodity Markets*, Vol. 27, 100223, doi: 10.1016/j.jcomm.2021.100223.

Sugimoto, K., Matsuki, T. and Yoshida, Y. (2014), "The global financial crisis: an analysis of the spillover effects on African stock markets", *Emerging Markets Review*, Vol. 21, pp. 201-233, doi: 10.1016/j.ememar.2014.09.004.

Tiwari, A.K., Aye, G.C., Gupta, R. and Gkillas, K. (2020), "Gold-oil dependence dynamics and the role of geopolitical risks: evidence from a Markov-switching time-varying copula model", *Energy Economics*, Vol. 88, 104748, doi: 10.1016/j.eneco.2020.104748.

Wen, D., Wang, Y., Ma, C. and Zhang, Y. (2020), "Information transmission between gold and financial assets: mean, volatility, or risk spillovers?", *Resources Policy*, Vol. 69, 101871, doi: 10.1016/j.resourpol.2020.101871.

World Health Organization (2020), "WHO coronavirus disease (Covid-19) dashboard- April 5", available at: https://covid19.who.int

Xu, W., Ma, F., Chen, W. and Zhang, B. (2019), "Asymmetric volatility spillovers between oil and stock markets: evidence from China and the United States", *Energy Economics*, Vol. 80, pp. 310-320, doi: 10.1016/j.eneco.2019.01.014.

Yavas, B.F. and Rezayat, F. (2016), "Country ETF returns and volatility spillovers in emerging stock markets, Europe and USA", *International Journal of Emerging Markets*, Vol. 11 No. 3, pp. 419-437, doi: 10.1108/ijoem-10-2014-0150.

Yoon, S.M., Al Mamun, M., Uddin, G.S. and Kang, S.H. (2019), "Network connectedness and net spillover between financial and commodity markets", *The North American Journal of Economics and Finance*, Vol. 48, pp. 801-818, doi: 10.1016/j.najef.2018.08.012.

Zhang, H., Cisse, M., Dauphin, Y.N. and Lopez-Paz, D. (2017), *"mixup: beyond empirical risk minimization"*, arXiv preprint arXiv:1710.09412.

Further reading

Albulescu, C.T., Aubin, C., Goyeau, D. and Tiwari, A.K. (2018), "Extreme co-movements and dependencies among major international exchange rates: a copula approach", *Quarterly Review of Economics and Finance*, Vol. 69, pp. 56-69, doi: 10.1016/j.qref.2018.03.007.

Author 1 (1989), "Regulatory policies", *Journal of Financial Services Research*, Vol. 3 Nos 2-3, pp. 211-246, doi: 10.1007/bf00122803.

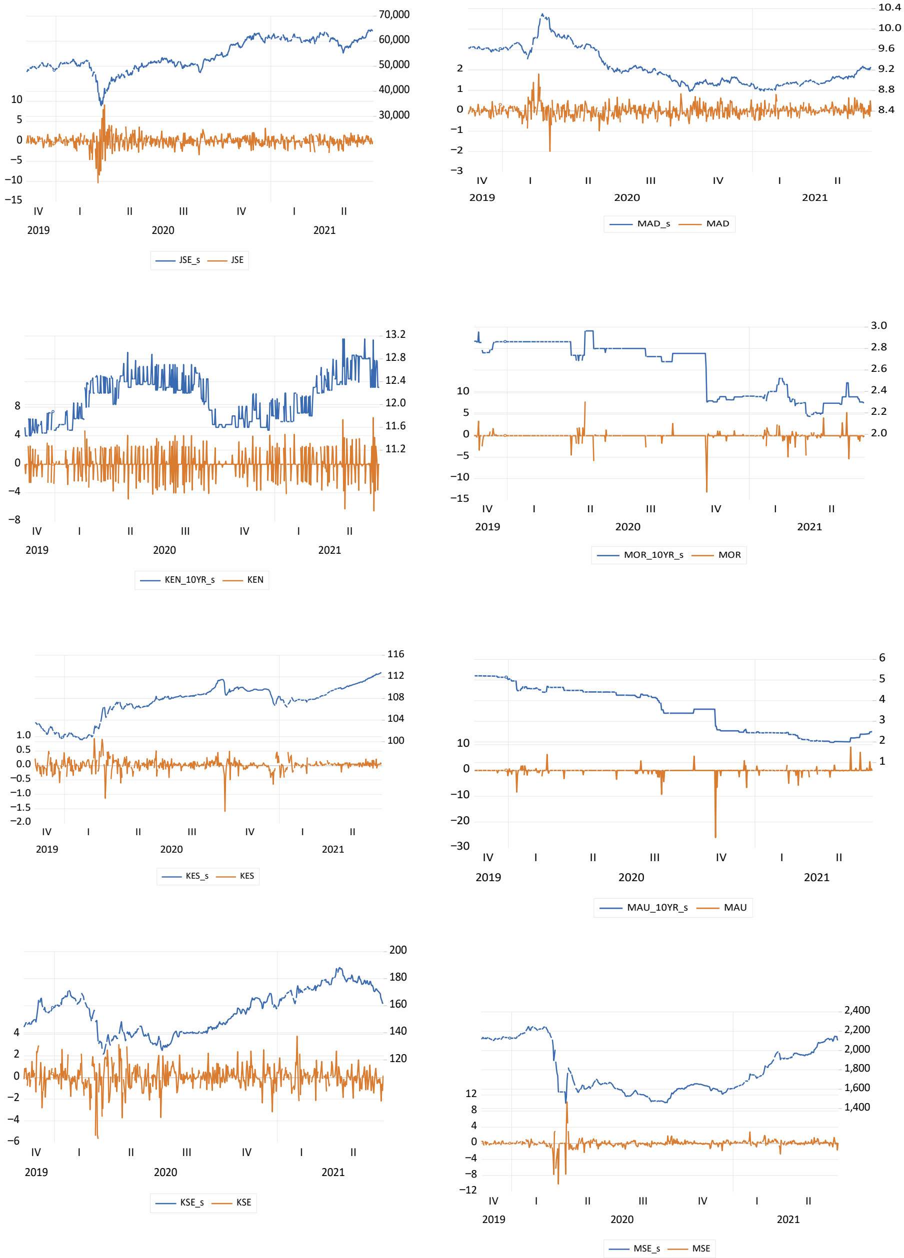
Cable News Network (2020), "Cable news network business", available at: https://edition.cnn.com/business/live-news/stock-market-news-today-032320/index.html.

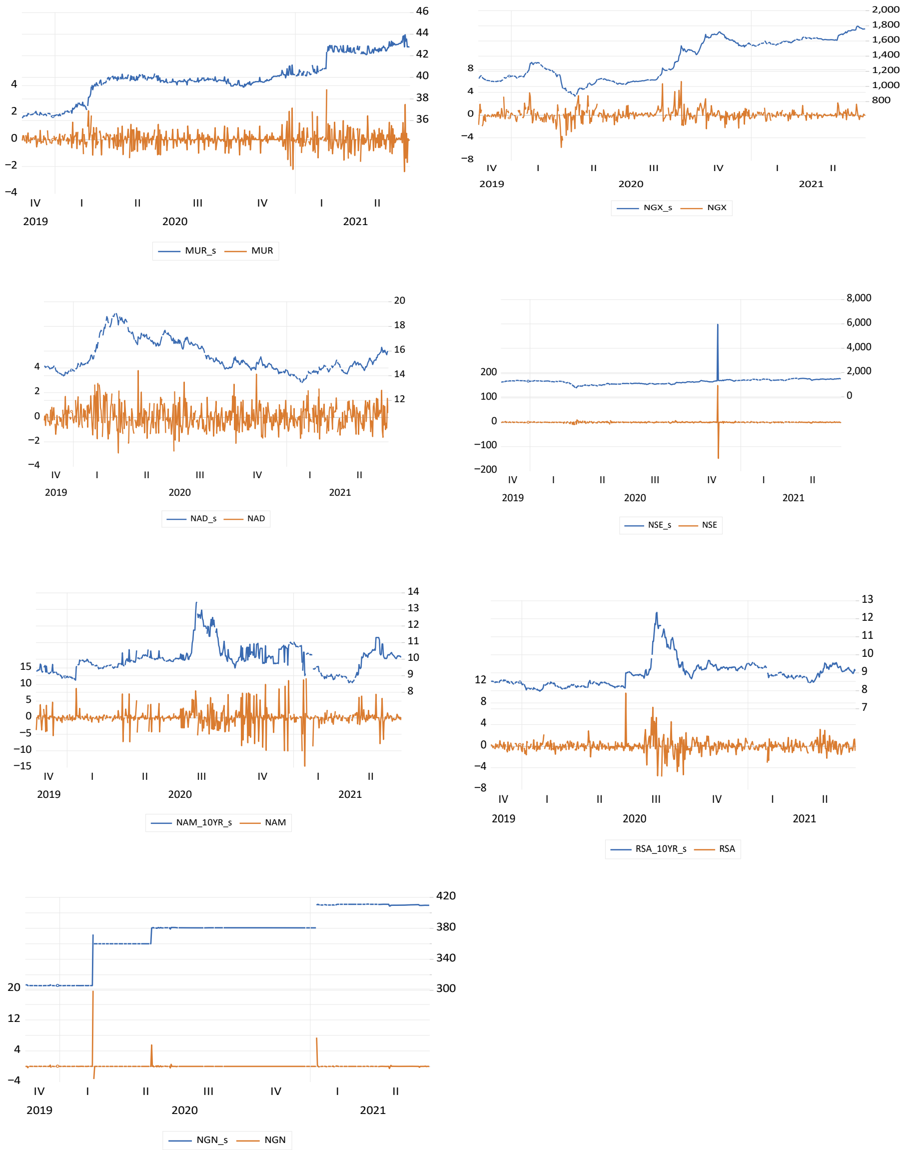
Li, X. and Wei, Y. (2018), "The dependence and risk spillover between crude oil market and China stock market: new evidence from a variational mode decomposition-based copula method", *Energy Economics*, Vol. 74, pp. 565-581, doi: 10.1016/j.eneco.2018.07.011.

United Nations Conference on Trade and Development (2020), "Global investment trend monitor", No. 39.

Corresponding author
Lord Mensah can be contacted at: LMensah@ug.edu.gh

Appendix
Dynamics of asset price series and their returns



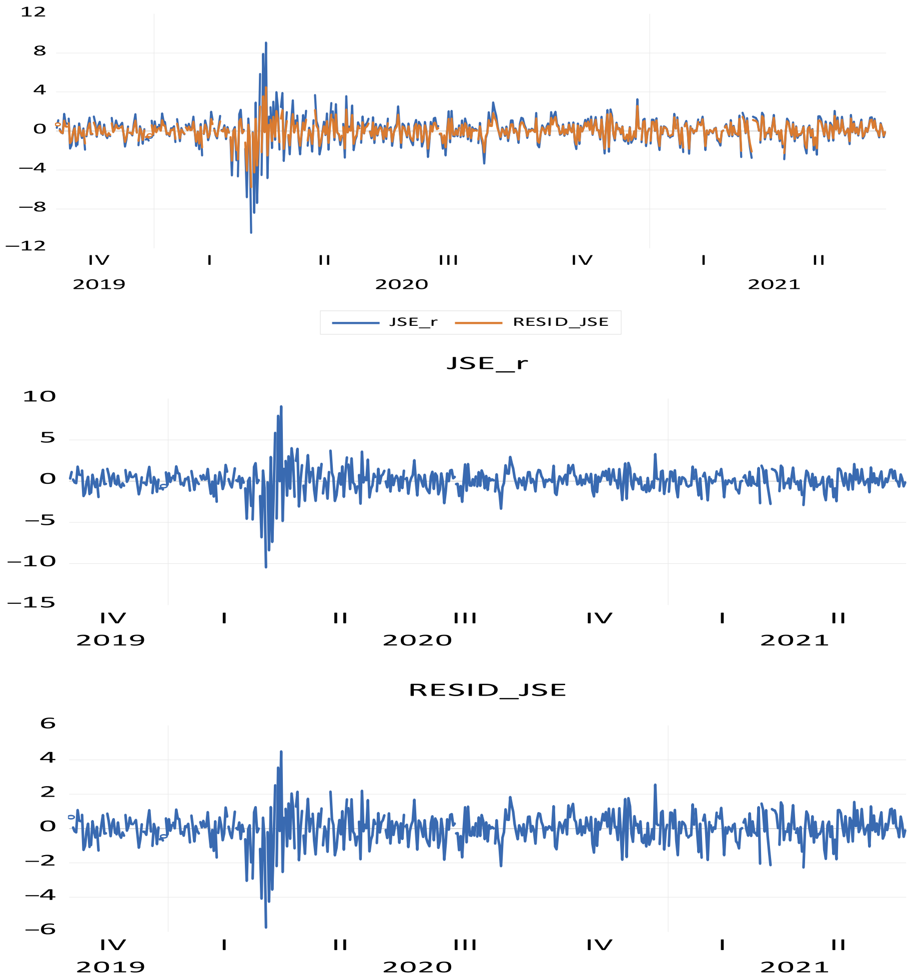


Note(s): On each graph, the blue line represents the asset prices over time, and the brown represents returns
Source(s): Appendix figure by authors (2023)

Annexure

I would like to, however, bring to your attention that, we used the residual series, extracted from an estimated or fitted EGARCH model, which mimic the calculated return series. When you fit a GARCH model, you can extract the residual series (returns) and the variance series (volatility). The figures below show the graphs (separately and combined) of the return series (JSE_r) and residual series from fitted EGARCH model (RESID_JSE) of the Johannesburg stock index, as an example.

Graph of fitted EGARCH model residual series VS log return series.



You would notice that the two series follow a similar pattern or trend. However, we have used the return series for all the analysis in the current, not the residuals. **You would also notice in the previous analysis; we found the total systemic risks to be** 18.20%. **But in the current analysis, using return series, we found the systemic risks to be** 21.50%.