Korsah and Kwadwo Danso
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Immune or vulnerable? African stock markets' response to U.S.–China trade wars and geopolitical tensions

David Korsah[1*] and Seth Kwadwo Danso[1]

Abstract

This study examines the dynamic impact of the U.S.–China trade war and geopolitical risks on African stock market returns. Using Wavelet Coherence analysis and the Quantile Vector Autoregression (QVAR) model, we capture both time–frequency dynamics and regime-specific connectedness. Drawing on data from seven major African stock exchanges, Geopolitical Risk (GPRI) and U.S.–China Trade Tension (UCTI) indices from January 2007 to February 2024, the results reveal that African markets are not immune but exhibit state-dependent vulnerability. During calm market conditions, trade tensions dominate as the main shock transmitter, whereas geopolitical risks become more influential in crisis periods. The Johannesburg Stock Exchange (JSE) emerges as a key transmitter of shocks, while the Nigerian Exchange (NGX) remains the largest receiver. These findings underscore the need for targeted regional risk management and coordinated policy responses to enhance Africa's financial resilience against external shocks.

Keywords U.S.–China trade war, Geopolitical risk, African stock markets, Wavelet coherence, Quantile VAR, Spillover

Introduction

The trade war between the United States and China has introduced unprecedented volatility into global financial markets, creating ripple effects that extend far beyond the two economic superpowers [1]. This rivalry crystallized into open confrontation in 2018, when the Trump administration imposed tariffs on approximately $360 billion worth of Chinese goods, citing unfair trade practices and intellectual property theft [2]. In retaliation, China imposed significant tariffs on U.S. agricultural and manufactured exports, consequently exacerbating and prolonging the trade war.

Beyond tariffs, the rivalry escalated into restrictions on technology transfers, with Huawei and other Chinese firms facing sanctions and access barriers to U.S. semiconductors [3]. The Biden administration reinforced this decoupling route by enacting the CHIPS and Science Act in 2022, restricting U.S. firms from supplying advanced chips to China. These measures underscore that the tension is no longer limited to trade but extends to financial markets, strategic industries, and global governance, intensifying broader geopolitical tensions that further complicate the global economic ecosystem.

Indeed, the ramifications of this trade-war are far-reaching. Global supply chains have been reconfigured, commodity markets destabilized, and financial flows redirected [4]. For Africa, whose economies are deeply integrated into commodity exports and increasingly tied to Chinese investment and U.S. aid, the repercussions are particularly acute [5, 6].

Africa's vulnerability to ongoing trade-war and othe related economic tensions shocks stem from the continent's dual dependency on both China and the U.S. China has emerged as Africa's largest trading partner, with trade surpassing $250 billion in 2022 [7]. This includes significant infrastructure financing under the Belt and Road Initiative (BRI), resource-for-infrastructure deals, and growing foreign direct investment [8].

*Correspondence:
David Korsah
Davek347@gmail.com
[1] University of Ghana, Accra, Ghana

The U.S., while no longer Africa's largest trade partner, remains a critical player through initiatives such as the African Growth and Opportunity Act (AGOA), direct investment, and development financing. U.S. financial institutions and aid agencies also play a stabilizing role, especially in financial governance and institutional strengthening [9].

This dual dependency places the African economy in general, and the stock markets in particular, in a precarious position. Evidence abounds that a slowdown in Chinese demand reduces commodity export revenues [10, 11], while U.S. monetary tightening leads to capital outflows and currency depreciation [12]. For instance, African currencies such as the Ghanaian cedi and the Nigerian naira experienced sharp depreciations in 2022, driven by aggressive interest rate hikes by the U.S. Federal Reserve, which in turn eroded investor confidence in local equities [13, 14]. Moreover, rising geopolitical tensions, particularly between the U.S. and China, the ongoing Russia–Ukraine war as well as the heightened tension in the Middle East have introduced an additional layer of uncertainty, influencing investor sentiment and cross-border capital allocation in ways that directly affect African financial stability.

While Africa's structural vulnerabilities remain significant, there is growing evidence of resilience and strategic adaptation [15, 16]. Policymakers are increasingly turning to regional frameworks such as AfCFTA, which promises to create the largest free trade area in the world, integrating over 1.3 billion people with a combined GDP of $3.4 trillion [17]. By reducing intra-African trade barriers, the agreement seeks to reduce dependency on external powers. Similarly, African central banks have also adopted countercyclical measures to mitigate external shocks. The South African Reserve Bank, for example, has strengthened its inflation-targeting regime, while Ghana and Nigeria have sought IMF support to stabilize reserves. Additionally, African stock exchanges have recorded an increasing spate of modernization through digitalization and regional integration [18]. The African Exchanges Linkage Project (AELP), launched in 2021, seeks to connect seven African bourses to facilitate cross-border trading, potentially deepening liquidity and resilience [19]. It goes without saying that the aforementioned drastic measures aim at invariably shoring up the continent's immunity to external shocks, including those amplified by geopolitical tensions.

From the foregoing, it is abundantly evident that there is a bone of contention in the literature on the resilience or otherwise of the African stock market to external shocks. Many studies observed that, generally, the African stock market is immune from external shocks, consistent with the decoupling theory. Evidently, Dooley and Hutchison [20] postulate that emerging markets, particularly the African stock exchange, exhibited a high degree of immunity to shocks from advanced countries, citing the Global Financial Crisis (GFC). This has been confirmed by several studies, notably Boako and Alagidede [21] and Korsah et al. [22], advancing that emerging markets are somewhat insulated from external shocks. Contrary to the assertions by decoupling theorists, Korsah and Mensah [23] and [24, 25] observed that emerging markets, especially Africa, cannot insulate themselves from the attendant repercussions of global shocks. Clearly, the absence of convergence of findings on the African stock market and external shocks reinforce the need for this study.

Further, to the best of our knowledge, existing studies have failed to delve into U.S.–China trade wars and the African stock market dynamics. Noteworthy exceptions on the U.S.–China trade war and African financial nexus focused primarily on U.S.–China trade war and inflation [26], U.S.–China trade war and exchange rate dynamics ([27]).

Moreover, while geopolitical risks are increasingly recognized as critical determinants of financial market behavior [22, 23], their specific interaction with U.S.–China tensions and African market responses remains underexplored. This makes the study particularly crucial, given evidence that geopolitical tensions have intensified globally since the U.S.-led invasion of Iraq in 2003 [28].

It is worthy of emphasis that the apparent absence of literature on the impact of external shocks, particularly the heightened U.S.–China trade war and geopolitical risks on stock markets in Africa leaves much to be desired, given that the African financial market is arguably one of the most preferred investment destinations [29, 30]. Further, like other financial markets across the globe, the increased capital flow, coupled with declined information asymmetry in Africa, has deepened integration within and across markets. This has, thus, increased the susceptibility of African markets to spillover of shocks from other sectors and jurisdictions, hence the need for this study.

Moreover, whereas prior studies have primarily examined different shocks in isolation, a comprehensive analysis of spillovers and connectedness among African stock markets, geopolitical risks, and the U.S.–China trade war remains largely underexplored.

Against this backdrop, this study seeks to examine the impact of the ongoing U.S.–China trade war and geopolitical risks on the African stock market. To put in proper context, this study seeks to:

(1) Examine the interconnectedness and the spillover effect among U.S.–China trade, geopolitical tensions and the African stock market.
(2) Assess the time and frequency dynamics of the spillover effects of U.S.–China trade war, and geopolitical risk on the African stock market.
(3) Identify stock markets that are more resilient to macroeconomic shocks as well as those vulnerable uncertainties.

This study stands out in the literature as the first of its kind to explore the interconnection between U.S.–China rivalry and concomitant geopolitical tensions with African financial market dynamics. Additionally, this study distinguishes itself in the literature by combining the novel Quantile Vector Autoregression (QVAR) model with Wavelet Coherence Analysis, a methodological approach rarely applied together. The QVAR framework captures nonlinear and asymmetric dynamics of stock returns under bearish, normal, and bullish market conditions, offering deeper insights into tail dependence and extreme events. Complementarily, the wavelet technique uncovers how macroeconomic shocks and stock market returns interact across different time scales, providing a more comprehensive understanding of spillovers and connectedness.

This research contributes to both academic and policy debates. Academically, it expands the literature on emerging market vulnerability to external shocks by focusing specifically on Africa, a region often marginalized in global finance research (Korsah et al.,[22, 31]). By contextualizing Africa within the U.S.–China rivalry and rising geopolitical friction, the study highlights how global power struggles cascade into developing regions.

For policymakers, the study provides insights into the vulnerabilities and resilience mechanisms of African financial systems, thus facilitating the formation of informed strategies for risk management, diversification, and institutional strengthening amidst compounded trade and geopolitical shocks. For investors, the research brings to bear markets that are relatively more resilient to shocks, highlighting viable investment destinations.

The rest of the paper is organized as follows: A critical review of empirical and theoretical literature is presented in Sect. ”Literature review”. Sect. ”Data and methodology” delves into methodological framework of the study, while section presents the empirical findings. Finally, Sect. “coupling/contagion theory” provides the conclusion of the study, policy implications, limitations as well as recommendation for future studies.

Literature review

Theoretical review

The theoretical underpinnings of how external shocks transmit to domestic financial markets are rooted in several interconnected frameworks. The debate often centers on the concepts of coupling versus decoupling.

Decoupling hypothesis

The decoupling hypothesis posits that business cycles and financial markets in emerging economies have become increasingly independent from those in advanced nations, driven by robust domestic demand, South-South trade, and improved macroeconomic policies [20]. This theory suggests that emerging markets, including those in Africa, could exhibit a degree of immunity to financial shocks originating in developed countries. Proponents argue that lower financial market integration and developmental differences can insulate these markets, allowing them to “decouple” and serve as a stable engine of global growth even during crises in the West [21].

Coupling/contagion theory

Conversely, the coupling or contagion theory argues that in an era of globalization, financial markets are more interconnected than ever. This school of thought emphasizes channels of transmission such as trade linkages, financial flows, and investor sentiment. Through the trade channel, a slowdown in major economies like China reduces demand for commodities, depressing export revenues and corporate earnings for African resource-exporting nations [32]. The financial channel operates through capital flows,monetary tightening in the U.S. (e.g., interest rate hikes) can trigger capital flight from riskier emerging markets, leading to currency depreciation and stock market declines [12, 14]. This is often explained by portfolio rebalancing and a global “risk-on, risk-off” sentiment among investors.

More recently, the literature has incorporated Geopolitical Risk (GPR) as a critical theoretical determinant of financial market behavior. Caldara and Iacoviello [28] formally define GPR as the risk associated with wars, terrorism, and international tensions that disrupt the normal course of international relations. Heightened GPR increases global risk aversion, leads to safe-haven flows into assets like the U.S. dollar, and dampens investment and trade, thereby affecting asset prices worldwide. The U.S.–China rivalry is a quintessential manifestation of such a risk, blending trade policy uncertainty with deep-seated geopolitical competition [22, 23].

These theoretical channels establish that African markets are potentially exposed to external shocks. However, their relative sensitivity, that is whether they are primarily coupled or decoupled, and how this relationship varies across different market conditions (bullish, normal, bearish) remains a contested and empirical question.

Empirical review

Global shocks and financial markets

Empirical evidence on the impact of global shocks on financial markets is vast but predominantly focused on developed and large emerging markets. Studies consistently show that events like the Global Financial Crisis (GFC) and the European Sovereign Debt Crisis led to significant cross-market contagion [33]. More recently, research has turned to trade policy uncertainty (TPU). Baker, Bloom, and Davis [34] developed a TPU index and demonstrated its negative impact on investment and employment in the U.S. Fajgelbaum and Khandelwal [35] found that the U.S.–China trade war led to significant declines in stock returns for firms exposed to tariff increases. Similarly, Korsah et al. [22] showed that spikes in their Geopolitical Risk index are associated with lower stock returns and higher volatility in international markets.

External shocks and African financial markets

The empirical evidence specific to Africa is mixed, reflecting the core theoretical debate. Several early studies, examining periods like the GFC, found support for the decoupling hypothesis. For instance, Boako and Alagidede [21] found limited volatility spillover from advanced markets to major African bourses, suggesting a degree of insulation.

However, a growing body of more recent literature challenges this view, arguing that Africa's deepening integration into the global economy has increased its vulnerability. Studies have shown that U.S. monetary policy shocks significantly impact capital flows and exchange rates in key African economies like Nigeria and Ghana [12, 13]. Furthermore, a slowdown in Chinese economic growth or demand has been directly linked to reduced commodity export revenues, fiscal pressures, and subsequent negative performance in African stock markets [36]. The aggressive U.S. Federal Reserve rate hikes in 2022, which led to sharp depreciations of the Ghanaian cedi and Nigerian naira, eroded investor confidence in local equities, providing a clear example of financial channel contagion [14].

U.S.–China trade war, GPR, and African markets

Despite this progress, a significant empirical gap remains. Existing studies on Africa have largely focused on isolated shocks: U.S. monetary policy, Chinese growth, or broad global risk aversion. The specific, compounded impact of the U.S.–China trade war and associated geopolitical tensions on African stock markets is severely underexplored.

The few exceptions that touch on this nexus do so indirectly. For example, Emegha et al. [26] focused on the impact of U.S.–China tensions on inflation in Africa, while Xu and Lien [27] examined exchange rate dynamics. However, a direct analysis of stock market returns is missing. Moreover, previous studies have often treated markets as homogeneous and shocks as linear. The emerging consensus is that financial contagion is asymmetric and regime-dependent, spillovers are often stronger during market downturns or periods of high volatility than during tranquil periods [33]. Yet, no study has applied a quantile-based approach to investigate how the spillovers from U.S.–China tensions and GPR to African markets differ between bullish, normal, and bearish states.

Hypothesis development

Building on the theoretical debate between coupling and decoupling, and the mixed empirical evidence, this study formalizes its expectations through testable hypotheses. The application of Wavelet Coherence and Quantile VAR methodologies allows for a nuanced investigation that moves beyond linear and static assumptions, leading to the following hypotheses:

H1: African stock markets exhibit significant time–frequency co-movement with U.S.–China trade tensions and geopolitical risks, with coherence clustering around major global events.

H2: The connectedness and spillover effects between U.S.–China tensions, geopolitical risks, and African stock returns are asymmetric and state-dependent, varying significantly across bullish, normal, and bearish market regimes.

H3: The primary transmitter of shocks to African markets is state-dependent: U.S.–China trade tensions (UCTI) dominate during calm market regimes, while geopolitical risk (GPRI) becomes the paramount transmitter during crisis periods.

H4: Within the African financial system, more developed and internationally integrated exchanges (e.g., JSE) will act as net transmitters of shocks, while less liquid and more domestically oriented exchanges (e.g., NGX) will function as net receivers.

Data and methodology

Data

The study draws on data from seven African stock exchanges, with at least one exchange selected from each of the continent's five geographical zones to ensure fair representation. The Egyptian Exchange (EGX, Egypt) and the Casablanca Stock Exchange (CSE, Morocco) represent North Africa; the Johannesburg Stock Exchange (JSE, South Africa) represents Southern Africa; the Nairobi Securities Exchange (NSE, Kenya) and the Dar es Salaam Stock Exchange (DSE, Tanzania) represent East Africa; while the Ghana Stock Exchange (GSE, Ghana) and the Nigerian Exchange (NGX, Nigeria) represent West Africa. The selection of these markets is also justified by their relative market capitalizations. According to CEIC data (July 2023), the combined capitalization of Africa's 29 stock exchanges stood at approximately US$1.6 trillion. Of this, the JSE accounted for US$1.356 trillion, NGX for US$45.9 billion, CSE for US$63.6 billion, EGX for US$31.2 billion, NSE for US$11.54 billion, GSE for US$6.55 billion, and DSE for US$6.2 billion. Collectively, these seven markets represent about 95% of the continent's total market capitalization. Stock market data, obtained from Bloomberg, are compiled at a monthly frequency.

The macroeconomic shock indexes, namely Geopolitical Risk Index (GPRI) and U.S.–China Trade war (UCTI) were sourced from http://policyuncertainty.com. GPRI is constructed using a text-search algorithm, which tracks articles and news on war, terrorism, geopolitics, military and war-like events, with focus on eleven (11) leading newspapers in the US, UK and Canada. The higher the index, the greater the level of uncertainty. The U.S.–China Tension index (UCTI) is constructed by computing the share of articles discussing rising U.S.–China tension, in particular, the share of articles containing mention of (i) United States (or U.S.) and China (or Chinese), (ii) contentious issues in the bilateral relationship, and (iii) phrases indicating tension. It is worth noting that data on stock market returns and the two (2) global economic shock indexes under consideration. span from January 2007 to February 2024, with a monthly frequency.

Methodology

Bivariate wavelet coherence

To achieve the objectives of this study, we begin by employing the bivariate wavelet method. This technique is particularly suited for capturing the complex interconnections arising from both market fundamentals and transitory dynamics [37]. A key advantage of the wavelet approach is that it requires no prior transformation of time series data, while simultaneously decomposing the data into different time–frequency domains. This ensures the preservation of critical information and mitigates irregularities in data structure. Moreover, its graphical features allow analysts to identify whether market interlinkages occur in the short, medium, or long term. Applied in this context, the wavelet method provides valuable insights into the connectedness and co-movement between macroeconomic shocks and stock market volatility, offering investors a useful tool for making informed investment decisions.

Continuous wavelet transform

There are two basic categories of wavelet transforms: the continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT). Madeleno and Pinho (2012) underscored that the CWT is essentially used for extracting features, while the DWT basically helps to reduce noise and compress data. This study adopts the CWT to analyze co-movement of stock market volatility and macro-economic shocks, due to its ability to provide continuous representation of the signal in both time and frequency domains. Again, CWT coefficients often retain more intuitive meanings in terms of scales and time positions, making it easier to interpret results.

The wavelet function has a null mean which is localized in time and frequency. The Mother wavelet is given by:

$$\varphi_{\tau,q}(t) = \frac{1}{\sqrt{q}}\varphi\left(\frac{t-\tau}{q}\right) \tag{1}$$

where $\frac{1}{\sqrt{q}}$ is the normalization component that ensures unity in variance, t, q and τ denote the time, scale and time position parameters, respectively.

The Morlet wavelet, loosely regarded as one of the daughter wavelets, is helpful in identifying and isolating periodic signals (Grinstead et al. [38]). A typical Morlet wavelet is given by:

$$\varphi^{M}(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{\frac{-t^2}{2}} \tag{2}$$

where ω_0 is the central frequency of the wavelet. ω_0 is set at 6 as it provides a good balance between time and frequency localization [38, 39].

To ensure efficient examination of time–frequency dynamics of macro-economic shocks and stock market volatility, the researchers apply the bivariate concept, also known as wavelet coherence. To better appreciate wavelet coherence, the researchers consider the cross-wavelet transform, wavelet power spectrum and phase difference.

According to Ng and Chan [40], the cross-wavelet transform tool helps to examine covariance in the time–frequency domain. The cross-wavelet transform shows the area in time space with high common power. In this case, the cross-wavelet transform is used to examine the coherence between stock returns and the selected macroeconomic shock indicators.

The cross-wavelet transform is defined as follows:

$$W_{xy} = W_x(i,s)W_y^{*}(i,s) \tag{3}$$

where $W_x(i,s)$ and $W_y^{*}(i,s)$ denote the cross-wavelet of series $x(t)$ and $y(t)$, respectively. * indicates a complex conjugate, i is the location parameter, and s is the scale dilation of the parameter.

The modulus of cross-wavelet transform could be derived from the wavelet power spectrum (WPS). WPS brings to the fore areas in the time–frequency space characterized by high common power. Essentially, WPS depicts the presence of local covariance between two time series data [41], in this case between stock market volatility and macro-economic shocks. The WPS is basically the squared absolute value of a specific time series, expressed by,

$$WPS_x(i,s) = [w_x(i,s)]^2 \tag{4}$$

Wavelet coherency, widely regarded as the equivalence of correlation coefficient, is well defined as the squared absolute value of normalizing a wavelet cross-spectrum to a single wavelet power spectrum. In line with Torrence and Webster [42], the squared wavelet co-efficient is expressed as follows:

$$R^2(x,y) = \frac{\left|\rho\left(s^{-1}W_{xy}(i,s)\right)\right|^2}{\rho\left(s^{-1}|W_x(i,s)|^2\right)\rho\left(s^{-1}\left|W_y(i,s)\right|^2\right)} \tag{5}$$

where ρ indicates a smoothing factor, which balances resolution and significance. A value close to 0 specifies a weak relationship, while a value close to 1 indicates a strong relationship. A stronger correlation or dependency is demonstrated by a hotter colour. The statistical significance of the coherence is inspected by the Monte Carlo procedure since the theoretical distribution of the cross-wavelet transforms coefficient is unknown. Furthermore, the bias problem in the wavelet power spectrum and wavelet cross-spectrum is eliminated by the normalizing function of the wavelet coherence.

WTC phase difference

The wavelet transforms coherence phase difference indicates the interruptions in the oscillation concerning the examined time series. Following Bloomfield et al. [43], the phase difference between $x(t)$ and $y(t)$ is represented as follows:

$$\begin{aligned}&\emptyset_{xy}(i,s)\\ &= \tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}W_{xy}(i,s)\right)\right\}}{\Re\left\{S\left(s^{-1}W_{xy}(i,s)\right)\right\}}\right) \quad \emptyset_{xy}(i,s) \in [-\pi, \pi]\end{aligned} \tag{6}$$

where $\Im$ and $\Re$ are the imaginary operators and real operator, respectively, and W_{xy} represent the cross-wavelet transform. In the wavelet coherence map, the dimensional phase pattern defines the effects of the wavelet coherence difference. The dimensional arrows are used to distinguish difference phase patterns. Right-pointing arrows (→) and left-pointing arrows (←) show whether two (2) time series variables are in phase (move in the same direction) and antiphase (move in the different directions), respectively. Right arrows pointing upwards (↗) and left arrows pointing downward (↙) indicate that the first variable is lagging. Conversely, left arrows pointing upward (↖) and right arrows pointing downward (↘) depict that the first variable is leading.

QVAR model

In analyzing returns connectedness and spillovers, we first and foremost compute the continuous compounding returns for the various stock markets as follows;

$$y_t = ln\left[\frac{P_t}{P_{t-1}}\right] * 100 \tag{7}$$

where y_t denotes monthly returns, P_t represents current price/current index of the respective markets whereas P_{t-1} denotes previous month's price/index [44, 45].

The QVAR model, developed from the VAR model framework, decomposes H-step ahead forecast-error variance for each variable of an N-dimensional VAR. This is based on the Generalized Forecast Error Variance Decomposition (GFEVD) framework propounded by Koop et al. [46] and Pesaran and Shin [47].

Accordingly, the QVAR process pth order is given as;

$$y_t = c(\tau) + \sum_{i=1}^{\rho} \beta_i(\tau)y_{t-1} + e_t(\tau), t = 1, 2, \ldots..T \tag{8}$$

where y_t is the endogenous variable to be estimated; $c(\tau)$ is the constant parameter of the τth quantile; $\beta_i(\tau)$ and $e_t(\tau)$ are the coefficient of the lagged dependent variable of the τth quantile, and idiosyncratic error, identically and independently distributed, respectively.

The Moving Average (MV) representation of the QVAR (Eq. 8) is estimated by;

$$y_t = (\tau) + \sum_{i=1}^{\infty} \emptyset_i(\emptyset)e_{t-i}(\tau) \quad t = 1, 2, \ldots, T \tag{9}$$

where; $\emptyset_i$ is the coefficient of the MV, recursively computed as;

$$\emptyset_i =_1 \emptyset_{i-1} +_2 \emptyset_{i-2} + \ldots +_p \emptyset_{i-p} \tag{10}$$

It is worth noting that the coefficient of the MV helps in the attribution of variance to individual variables in the system.

The GFEVD, accounting for the contributions of variable "*j*" to the H-step ahead forecast error variance of a given variable, say "*i*", is given as;

$$d_{ij}^{H} = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i\emptyset_i(\tau)\sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i\emptyset_i(\tau)\sum e_i\right)} \quad (11)$$

where $_{jj}$ is the jth diagonal component of the standard deviation and $\sum$ is the covariance matrix of errors. For a given ith component, e_i is a selecting vector with ith element and zero otherwise.

Following Diebold and Yilmaz [33], the study builds a connectedness table, to ascertain pairwise and net connectedness of the variables, ie stock market volatilities and macroeconomic shocks.

The population connectedness table.

Connectedness Table Schematic.

Variables	Y_1	Y_2	…	Y_N	From others
Y_1	d_{11}^H	$[d_{12}^H$	…	d_{1N}^H	$\sum_{j\neq 1} d_{1j}^H$
Y_2	d_{21}^H	d_{22}^H	…	d_{2N}^H	$\sum_{j\neq 2} d_{2j}^H$
…	…	…	…	…	…
…	…	…	…	…	…
…	…	…	…	…	…
Y_N	d_{N1}^H	d_{N2}^H	…	d_{NN}^H	$\sum_{j\neq N} d_{Nj}^H$
To others	$\sum_{i\neq 1} d_{i1}^H$	$\sum_{i\neq 2} d_{i2}^H$	…	$\sum_{i\neq N} d_{iN}^H$	$\sum_{i\neq j} d_{ij}^H$

Source: Table courtesy of [33].

Given that summation of the row is not equal to 1, the spillover index is calculated by normalizing the variance decomposition matrix by the row sum. Thus, the spillover index from "*j*" to "*i*" is given by;

$SI_{ij}^{H} = \frac{d_{ij}^{H}}{\sum_{j=1} d_{ij}^{H}}$, where

$$\sum_{j=1}^{N} SI_{ij}^{H} = 1 \quad (12)$$

The net directional spillover between the markets is expressed as;

$$NTS_{ij}^{H} = d_{ji}^{H} - d_{ij}^{H} \quad (13)$$

Findings and analysis

Descriptive statistics

Table 1 presents the summary of the returns series of the stock markets under consideration, and the macroeconomic shock indicators (proxies), notably Geopolitical Risk Index (GPRI) and U.S.–China Trade war Index (UCTI). The statistics comprise the mean, median, maximum return, minimum returns, standard deviation (Std. Dev), skewness, kurtosis and observations (obs.).

The descriptive statisitcs from Table 1 suggests that the global uncertainty indices (GPRI and UCTI) exhibit high volatility and are characterized by significant positive skewness and high kurtosis, indicating a propensity for extreme positive spikes during crisis events that deviate sharply from typical conditions. In contrast, the African stock market indices demonstrate considerably lower volatility and are generally symmetrically distributed with kurtosis near normal levels, suggesting more stable return profiles; the notable exception is the DSE (Tanzania), which displays pronounced negative skewness and exceptionally high kurtosis, signaling a history of severe negative returns that are extreme outliers. Overall, the data captures 206 monthly observations from January 2007 to February 2024, effectively encompassing periods of significant financial stress and calm.

Wavelet coherence results and discussion

The wavelet coherence (WTC) analysis provides a vivid visualisation of the evolving and frequency-dependent

Table 1 Descriptive statistics for stock returns and macroeconomic shock indexes

Var	Mean	Median	Max	Min	Std. Dev	Skewness	Kurtosis	Obs
GPRI	101.05	90.96	318.95	58.42	35.68	1.70	5.50	206
UCTI	132.25	118.26	349.95	77.61	44.81	1.44	4.61	206
DSE	7.54	7.54	7.57	7.44	0.02	− 1.87	8.31	206
GSE	7.82	7.81	7.90	7.77	0.03	− 0.21	2.09	206
RSE	4.97	4.96	4.99	4.96	0.01	1.01	3.04	206
NGX	10.83	10.81	10.93	10.68	0.05	− 0.21	2.26	206
CSE	9.32	9.29	9.41	9.18	0.05	− 0.33	2.31	206
NSE	7.43	7.42	7.50	7.33	0.04	− 0.24	2.07	206
JSE	9.27	9.26	9.40	9.18	0.04	0.21	2.33	206

Source: Authors' own work

interaction between African stock market returns and global uncertainty indexes namely, the U.S.–China trade war index (UCTI) and the geopolitical risk index (GPRI). Unlike static correlation measures, WTC captures the degree of co-movement at different horizons and assesses whether global shocks lead or lag African markets over time.

The findings of the wavelet approach are presented in Figs. 1 and 2 below. The vertical axis of the plot displays the frequency (time-scale band), ranging from the highest to the lowest frequency while the horizontal axis provides the time domain for the stock returns. The extent of interdependence between the series is determined by the colour of the surface. Warmer colours (red) depict high correlation whereas cold colours (blue) indicates lower correlation/interdependence between the series. The zone for the edge effect is specified by the cone of influence (COI), of which beyond its boundaries coherence values become unreliable.

From Figs. 1 and 2, we observe that a striking feature of the WTC plots is that coherence is not constant across the sample period but clusters heavily around key geopolitical and trade-related events. The first major period of pronounced coherence appears during the escalation of the U.S.–China tariff war from the third quarter of 2018 through late 2019. This period corresponds to multiple waves of tariff impositions and retaliations, which significantly raised global uncertainty and disrupted trade flows, consistent with a study by Li et al. [48]. The coherence plots show large, persistent yellow–red patches during this interval, particularly at medium-to long-term periodicities (8–32 months). The phase arrows are predominantly down-right, indicating that the trade war led African stock market returns, which responded with a lag. This suggests that African markets, while not direct participants in the tariff war, were nonetheless indirectly affected through heightened global financial uncertainty, trade spillovers, and commodity price fluctuations in line with a related research by Korsah et al. [22] which revealed that African markets are not immune to external shocks, particularly from advanced economies.

The second window of intense coherence emerges in early 2020, coinciding with the signing of the Phase-One trade deal between the U.S. and China and the outbreak of the COVID-19 pandemic. From Figs. 1 and 2, it can be observed that while the agreement temporarily de-escalated trade tensions, uncertainty remained elevated because tariffs largely persisted and global supply chains remained fragile, consistent with Caliendo and Parro [49].

We further observed that, the COVID-19 pandemic added an additional layer of global risk, which is captured in the coherence plots as a continuation of strong co-movement between African stock markets and both UCTI and GPRI. Importantly, the arrows during this interval tilt down-right for both indices, showing that African markets reacted to these global policy shocks rather than shaping them, as contained in a study by Korsah and Mensah [23].

A careful observation of Figs. 1 and 2 reveals that a third coherence cluster occurs during late 2022 and into 2023, when the U.S. introduced sweeping semiconductor and advanced technology export restrictions targeting China. These measures reinvigorated trade and geopolitical tensions, contributing to renewed global policy risk. Again, the WTC plots highlight broad coherence at medium-term periodicities, with the trade war index leading African stock market returns. This is especially visible in the JSE (South Africa), which shows the deepest and most sustained bands of coherence, reflecting its stronger integration into global markets.

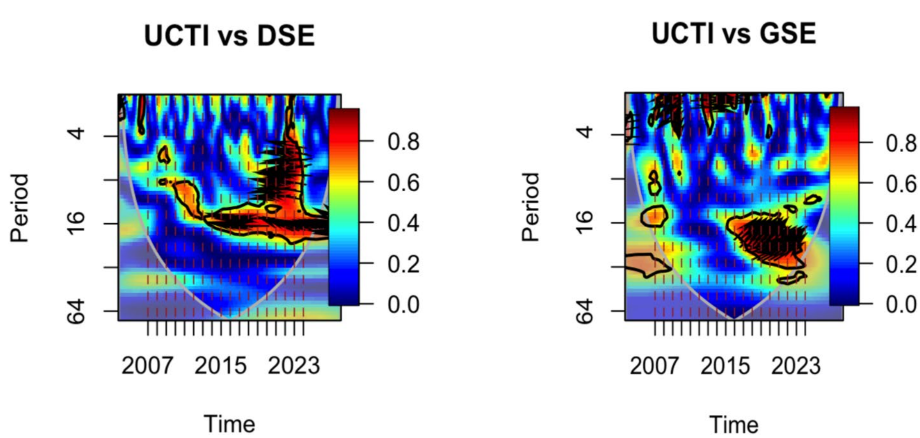

Fig. 1 Stock Market Returns and GPRI. Source: figure by authors

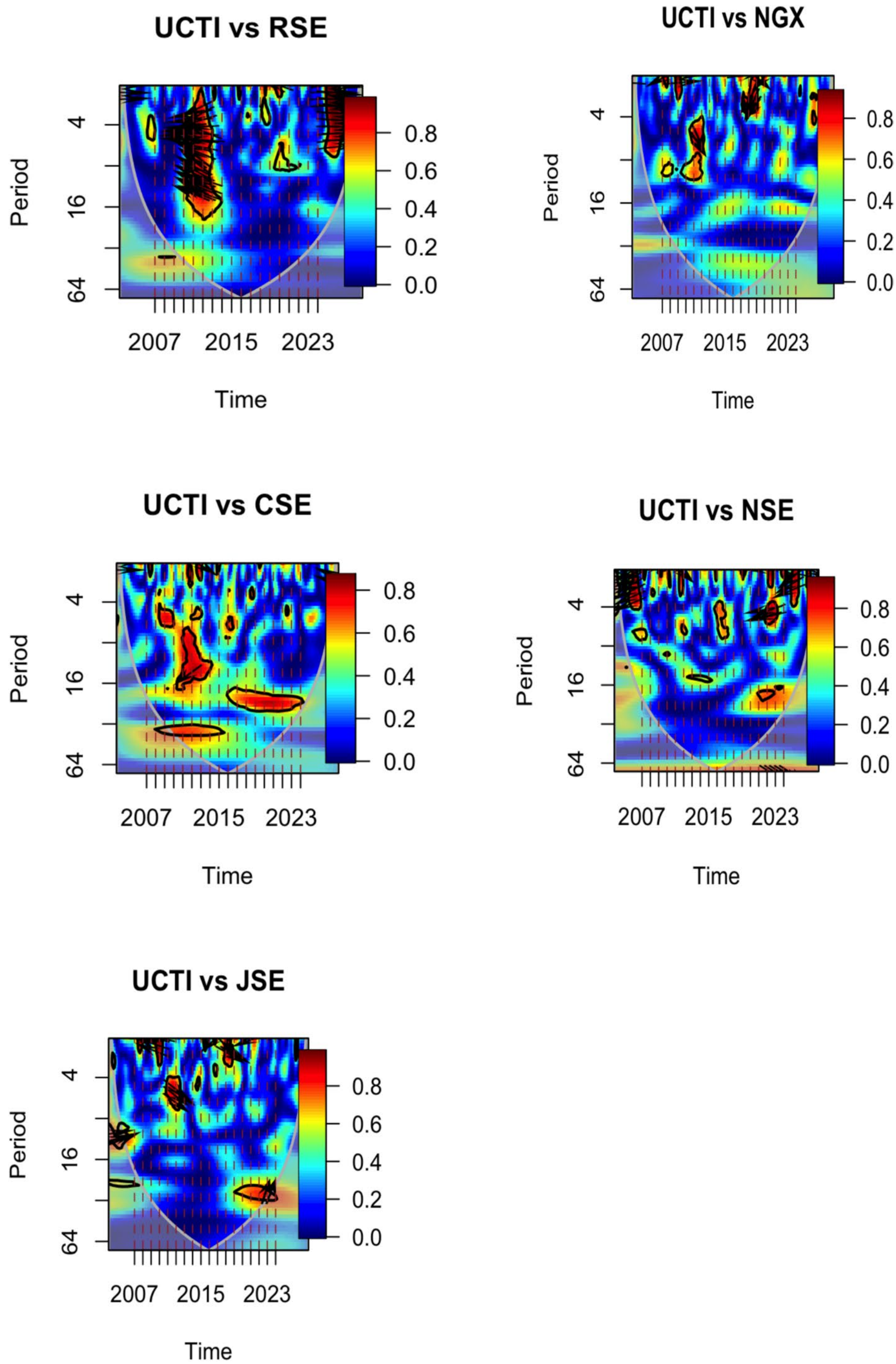

Fig. 2 Stock Market Returns and UCTI. Source: figure by authors

Across markets, the strength and persistence of coherence differ significantly. The JSE consistently emerges as the most globally sensitive market, exhibiting long-lasting coherence with both UCTI and GPRI at business-cycle frequencies. In contrast, the NSE (Nigeria) displays more episodic coherence, with significant bands concentrated during global stress events such as 2018–2019, early 2020, and late 2022. The phase arrows for the NSE suggest that it lags behind both UCTI and GPRI. Similarly, the EGX (Egypt) shows meaningful coherence around the same episodes, particularly at medium horizons, though with occasional anti-phase arrows indicating that local political or economic conditions can sometimes dampen or offset global influences.

Smaller and less globally integrated markets such as the CSE (Morocco), GSE (Ghana), RSE (Rwanda), and DSE (Tanzania) reveal weaker and more sporadic coherence. Nonetheless, significant patches appear during the tariff escalation of 2018–2019 and again in 2022–2023, demonstrating that no African market is entirely insulated from global policy uncertainty as postulated by [24, 25]. A careful observation of Figs. 1 and 2 reveal that the coherence in the said less integrated markets is generally short-lived and concentrated at medium horizons, reinforcing the decoupling theory. The NGX (Nigeria) shows a pattern similar to the NSE, albeit less pronounced.

The comparison between UCTI and GPRI highlights important asymmetries. In tranquil and typical market conditions, the wavelet coherence plots point to UCTI as the dominant driver of African stock market returns. This underscores the far-reaching influence of the U.S.–China trade war, which, despite being a bilateral conflict, generated global ripples that materially affected African markets [35]. However, during periods of elevated stress, such as the onset of the COVID-19 pandemic and the Russia–Ukraine conflict, GPRI's influence intensifies, sometimes surpassing that of UCTI.

The evidence from wavelet coherence analysis underscores that African stock markets are not immune [23] but rather highly vulnerable to global trade and geopolitical shocks. The vulnerability is, however, state-dependent.

Quantile VAR connectedness analysis

The quantile vector autoregression (QVAR) connectedness results complement the wavelet coherence evidence by showing how shocks propagate asymmetrically across African stock markets and global uncertainty indices under different market regimes.

Upper quantile ($\tau = 0.95$)

At the upper quantile ($\tau = 0.95$), representing a stressed or bullish state, the results in Table 2 reveal a marked shift in the connectedness landscape. Geopolitical risk (GPRI) emerges as the dominant external driver with a net connectedness of 41.33, consistent with findings that geopolitical turbulence such as the COVID-19 outbreak and the Russia–Ukraine conflict generate substantial spillovers into emerging equity markets [28, 50]. Nonetheless, U.S.–China trade tensions (UCTI) remain materially influential (+29.06), supporting evidence that trade-policy frictions disrupt returns even during broader crises [34, 35].

Economically, these magnitudes imply that a one-standard-deviation increase in geopolitical risk transmits roughly 41 percent of the forecast-error variance of African stock returns within a 3–5 month horizon, equivalent to a 45–60 basis-point fluctuation in monthly returns. Similarly, a comparable shock from the U.S.–China trade war accounts for nearly 30 percent of total volatility, corresponding to an average 25–40 basis-point swing in market performance.

The dual importance of GPRI and UCTI underscores the multidimensional vulnerability of African markets in stressed regimes, where geopolitical shocks amplify volatility while trade-policy uncertainty compounds risks.

Within African markets, the Johannesburg Stock Exchange (JSE) continues as the strongest net transmitter (+51.27), reflecting its systemic influence as a deep and liquid market, while the Nigerian Stock Exchange (NSE) remains the largest net receiver (−46.61), consistent with its higher exposure to external commodity and capital-flow shocks [51].

Table 2 Upper quantile directional return spillovers between equity markets returns in Africa and macroeconomic shock indexes (GPRI, UCTI) ($\tau = 0.95$)

	GPRI	UCTI	DSE	GSE	RSE	NGX	CSE	NSE	JSE	FROM
GPRI	**90.50**	1.70	0.37	0.38	0.64	0.54	0.42	1.45	4.00	9.50
UCTI	1.78	**78.86**	8.47	1.58	3.49	1.88	1.79	0.65	1.49	21.14
DSE	3.33	11.72	**49.23**	6.75	5.28	6.79	1.09	2.80	13.02	50.77
GSE	3.17	3.74	6.49	**37.40**	6.69	15.24	1.22	2.18	23.87	62.60
RSE	7.97	9.83	6.88	15.34	**44.53**	7.56	1.92	1.79	4.19	55.47
NGX	13.45	7.95	5.61	2.27	7.51	**50.06**	1.06	1.07	11.01	49.94
CSE	9.41	5.95	3.45	1.96	4.47	4.67	**60.67**	1.76	7.68	39.33
NSE	7.23	7.28	7.58	8.91	5.51	10.60	1.85	**41.00**	10.06	59.00
JSE	4.49	2.02	3.98	4.88	0.86	5.08	2.03	0.69	**75.96**	24.04
TO	50.83	50.20	42.83	42.07	34.44	52.36	11.37	12.40	75.31	371.80
NET	41.33	29.06	−7.95	−20.53	−21.04	2.42	−27.96	−46.61	51.27	**TCI** = 41.31

Source: Authors' own work

For investors, these results mean that crisis-driven surges in geopolitical uncertainty can erase between 3 and 5% of quarterly portfolio value if unhedged, while trade-policy shocks can further dampen cross-market liquidity and diversification benefits. For policymakers, they underscore the need for proactive countercyclical policy and regional liquidity buffers to absorb such external volatility.

The connectedness plot further illustrates bold spillover linkages from GPRI to multiple African markets, which parallels the wavelet coherence evidence showing pronounced short- and medium-term co-movements during crises. Together, these results confirm that geopolitical risks overshadow trade tensions as the dominant force in tail regimes, though both channels materially condition African stock market dynamics.

Median quantile ($\tau = 0.50$)

Table 3 presents the QVAR connectedness results for the median quantile ($\tau = 0.50$), corresponding to normal market conditions. The evidence suggests that U.S.–China trade tensions (UCTI) remain a significant driver of African stock markets. With a net connectedness of **+ 31.62**, UCTI continues to exert considerable influence, although its dominance moderates relative to the tranquil regime. This finding aligns with prior studies showing that trade policy uncertainty significantly affects emerging market returns through trade channels, commodity pricing, and global supply chains [34], Fajgelbaum & Khandelwal [35]). Geopolitical risk (GPRI) also plays a larger role under normal conditions, with a net connectedness of **+ 8.54**, suggesting that as markets operate under typical states, both geopolitical and trade-policy shocks interact in shaping stock return dynamics.

Interpreting these figures economically, a one-standard-deviation rise in U.S.–China trade tensions explains about 32 percent of variations in African returns over a 4-month horizon, corresponding to a 15–25 basis-point movement in monthly returns. Geopolitical risks contribute an additional 8–10 percent of return variation, translating to an approximate 10–15 basis-point swing. Thus, even in stable periods, global uncertainty drives measurable shifts in African equity valuations and investor risk premiums.

This result is consistent with evidence that geopolitical turbulence, even absent full-blown crises, raises global risk premia and reduces investors' willingness to hold risky assets [28, 50].

Within the African markets, the Johannesburg Stock Exchange (JSE) again emerges as the leading net transmitter (**+ 48.11**), confirming its systemic role as a regional amplifier of global shocks. As the most liquid and internationally integrated African exchange, the JSE often acts as a conduit for external shocks to spread into the continent (Boakye et al., [51]). Conversely, the Nigerian Stock Exchange (NSE) remains the largest net receiver (**− 44.59**), reflecting its vulnerability to global uncertainty spillovers and its structural dependence on commodity price cycles and capital inflows [52]. Other markets, notably the Casablanca Stock Exchange (CSE), Ghana Stock Exchange (GSE), and Rwanda Stock Exchange (RSE), register modest but negative net connectedness, indicating that they primarily absorb external shocks rather than transmit them, a pattern consistent with their relatively smaller size and lower international financial integration [19].

This result implies that portfolio exposure to the JSE amplifies volatility during global uncertainty, while investments concentrated in the NGX or GSE, though less globally integrated, face prolonged recovery times following international shocks. Collectively, these results

Table 3 Middle quantile directional return spillovers between equity markets returns in Africa and macroeconomic shock indexes (GPRI, UCTI) ($\boldsymbol{\tau} = 0.50$)

	GPRI	UCTI	DSE	GSE	RSE	NGX	CSE	NSE	JSE	FROM
GPRI	**90.44**	2.53	0.93	0.29	1.09	1.76	0.56	1.38	1.02	9.56
UCTI	0.74	**82.33**	7.67	1.16	4.04	0.70	1.36	0.82	1.18	17.67
DSE	1.47	9.10	**45.26**	12.18	5.54	11.89	1.10	1.60	11.86	54.74
GSE	0.52	2.15	9.39	**38.34**	6.39	17.57	1.22	2.18	22.25	61.66
RSE	2.98	11.78	9.30	10.36	**46.02**	7.72	3.25	3.94	4.65	53.98
NGX	2.87	7.28	10.97	7.86	7.49	**52.11**	1.91	1.82	7.70	47.89
CSE	3.33	5.72	3.69	1.61	4.55	3.05	**65.58**	3.15	9.33	34.42
NSE	3.62	6.91	10.20	8.45	5.66	14.16	2.10	**38.80**	10.10	61.20
JSE	2.57	3.82	2.65	2.65	1.44	2.59	2.52	1.75	**80.02**	19.98
TO	18.10	49.28	54.80	44.55	36.21	59.44	14.00	16.61	68.10	361.10
NET	8.54	31.62	0.06	− 17.11	− 17.77	11.55	− 20.42	− 44.59	48.11	**TCI** = 40.12

Source: Authors' own work

underscore that during normal market conditions, African stock markets remain highly sensitive to UCTI and GPRI, with transmission shaped by market depth and regional interconnectedness.

Lower quantile ($\tau = 0.05$)

Concentrating on Table 4 ie lower quantile regime, representing calm or bearish conditions ($\tau = 0.05$), we observe that the UCTI is the most influential external driver. With a net connectedness of + 46.30, UCTI emerges as the dominant transmitter of shocks, surpassing both GPRI and all the African stock markets. This suggests that even when global financial conditions are relatively stable, African markets remain sensitive to policy shocks originating from the U.S.–China trade conflict.

This level of connectedness implies that a one-standard-deviation increase in trade-war tension transmits about 46 percent of total return volatility to African markets within 3–6 months. In practical terms, this equates to an estimated 20–40 basis-point shift in average monthly returns, similar in scale to a moderate tightening of monetary policy by 25–50 basis points in domestic interest rates.

Among the African markets, the JSE (South Africa) also stands out as a strong transmitter of shocks (+ 39.66), reflecting its deep integration with global capital flows. On the other side, the NSE (Nigeria) is the largest net receiver (− 47.00), absorbing external shocks without transmitting much back to the system. Other markets such as CSE (Kenya), GSE (Ghana), and RSE (Rwanda) also record net negative positions, underscoring their dependence on global conditions rather than their ability to influence them.

GPRI plays a relatively muted role in this regime, with its transmission overshadowed by UCTI. In all, the coherence as displayed in Table 4 shows that in tranquil times, trade-war shocks dominate geopolitical risk shocks in shaping African market returns, confirming findings in a similar study by [24, 25].

From an investor standpoint, this result means that even under calm global conditions, an escalation in trade disputes can cause a measurable 0.2–0.4% decline in monthly returns across African equities. For policymakers, it highlights how trade-policy uncertainty functions as an external monetary constraint, limiting domestic financial stability despite stable local fundamentals.

Economic mechanism of state-dependent vulnerability

The asymmetric and state-dependent vulnerability of African stock markets to external shocks can be rationalized through the interaction of financial, trade, and behavioral transmission channels. During crisis regimes ($\tau = 0.95$), heightened risk aversion and flight-to-safety behavior dominate global financial flows. Consistent with modern portfolio theory [53] and global asset allocation models, investors reallocate capital toward advanced economies and safe assets, such as U.S. Treasuries or gold, when geopolitical uncertainty (GPRI) intensifies. This amplifies the impact of GPRI through the financial channel, as capital outflows and rising risk premiums depress African equity valuations. The resulting contagion is reinforced by information cascades [54], where herding among international investors magnifies market co-movements even in the absence of new local information.

By contrast, in calm or bearish regimes ($\tau = 0.05–0.25$), the U.S.–China trade tensions (UCTI) operate mainly through the real-trade and commodity channels. African economies, particularly those with export dependencies on raw materials, experience valuation shifts when

Table 4 Lower quantile directional return spillovers between equity markets returns in Africa and macroeconomic shock indexes (GPRI, UCTI) ($\tau = 0.05$)

	GPRI	UCTI	DSE	GSE	RSE	NGX	CSE	NSE	JSE	FROM
GPRI	**90.20**	3.01	1.08	0.59	1.04	1.53	0.44	1.19	0.91	9.80
UCTI	0.76	**80.35**	8.25	1.39	4.30	1.16	1.50	0.86	1.44	19.65
DSE	1.74	10.91	**45.26**	10.69	5.63	10.97	1.17	2.33	11.30	54.74
GSE	0.72	5.05	9.78	**35.86**	6.97	18.77	1.46	4.17	17.23	64.14
RSE	3.45	13.91	9.50	10.82	**44.55**	6.82	3.38	3.13	4.44	55.45
NGX	3.54	11.99	10.50	6.86	7.29	**46.65**	2.22	3.28	7.67	53.35
CSE	3.37	7.40	4.37	1.83	5.15	3.35	**63.39**	2.72	8.41	36.61
NSE	3.42	8.72	11.40	11.72	6.18	16.23	1.41	**34.04**	6.87	65.96
JSE	2.59	4.95	2.45	3.35	1.13	1.40	1.46	1.28	**81.39**	18.61
TO	19.60	65.95	57.33	47.26	37.69	60.22	13.04	18.95	58.27	378.32
NET	9.80	46.30	2.59	− 16.88	− 17.76	6.87	− 23.58	− 47.00	39.66	**TCI** = 42.04

Source: Authors' own work

trade-policy frictions disrupt global demand or alter commodity price expectations. These effects are transmitted to stock markets via corporate earnings revisions, exchange rate adjustments, and portfolio rebalancing in resource-linked sectors. Thus, under stable global financial conditions, UCTI exerts its strongest influence through changes in expected cash flows, rather than through investor sentiment or capital flight.

The regime dependence observed in the QVAR analysis therefore reflects nonlinear transmission mechanisms:In calm regimes, the trade-policy channel dominates, with UCTI shocks altering African market fundamentals through supply-chain disruptions and commodity price adjustments; in crisis regimes, the financial and behavioral channels prevail, where GPRI shocks trigger cross-border portfolio reallocation, herding, and liquidity withdrawal.

This dual mechanism aligns with recent evidence in the behavioral finance and global contagion literature [34, 50, 55], which posits that the strength and direction of shock transmission depend on the prevailing market sentiment regime. Accordingly, the QVAR results substantiate that African markets are not uniformly exposed to global shocks but are selectively vulnerable, depending on whether uncertainty originates from trade-policy realignments or from systemic geopolitical tensions.

From a policy perspective, this mechanism implies that macroprudential frameworks must differentiate between trade-related and geopolitical shocks. While trade tensions warrant structural diversification and export reorientation, geopolitical risks require capital flow management, liquidity support, and regional financial cooperation to mitigate flight-to-safety spillovers.

Implications of the findings

The QVAR connectedness results reveal strong regime-dependent asymmetries in how global uncertainties affect African stock markets, with important economic implications. At the lower quantile ($\tau = 0.05$), corresponding to tranquil or bearish markets, U.S.–China trade tensions (UCTI) dominate with a net connectedness of **+46.30**, surpassing both African markets and geopolitical risks (GPRI). This suggests that even in calm periods, African equities remain highly sensitive to trade-policy shocks [34], Fajgelbaum & Khandelwal [35]). Economically, this reflects the continent's dependence on global supply chains and commodity exports, where disruptions in trade policy transmit rapidly into stock market performance and investor confidence. In the median quantile ($\tau = 0.50$), representing normal market conditions, UCTI continues as the key driver (**+31.62**), though its influence moderates, while GPRI gains relative importance (**+8.54**). This indicates that both trade-policy and geopolitical risks jointly shape stock return dynamics under typical conditions [28, 50].

The implication here is that African markets are increasingly integrated into global financial systems, such that uncertainty abroad directly affects capital allocation, cross-border investment, and exchange rate stability. By contrast, in the upper quantile ($\tau = 0.95$), reflecting stressed or bullish regimes, GPRI emerges as the dominant transmitter (**+41.33**), overshadowing UCTI (**+29.06**) and highlighting the outsized role of global political shocks during crises such as COVID-19 and the Russia–Ukraine war [28]. For African economies, this points to heightened exposure to capital outflows, currency depreciation, and inflationary pressures during global political crises, which may undermine macroeconomic stability.

Across all regimes, the Johannesburg Stock Exchange (JSE) consistently acts as the strongest net transmitter, reflecting its systemic role as Africa's most liquid and globally integrated market. This underscores South Africa's position as a gateway for international investors into Africa, meaning that volatility originating in the JSE can quickly spill over to smaller, less liquid exchanges. Conversely, the Nigerian Stock Exchange (NSE) persistently absorbs shocks as the largest net receiver, underscoring its structural vulnerability to global uncertainty spillovers [19, 51]. This vulnerability signals that a persistent shock absorption may erode investor confidence, exacerbate capital flight, and reduce the effectiveness of domestic monetary policy in stabilizing financial markets.

Essentially, the findings highlight a regime-dependent vulnerability of African stock markets. That is, trade-policy shocks dominate in calm periods, both uncertainties matter under normal states, and geopolitical risks take precedence in times of crisis.

Net return connectedness network analysis

The network plot shown in Fig. 3 below provides a graphical representation/visualization of the extent of connectedness, the net receivers and transmitters of shocks, and the direction and intensity of the spillovers between the stock markets and indexes as presented in Tables 2–4.

To begin with, the size of the node represents the magnitude of shocks transmitted or received by a market, where as the colour depicts whether a variable is a net receiver of shocks (yellow) or a net transmitter of shocks/spillovers (blue). The arrows signify the direction of the spillovers. The deeper the colour of the arrow, the greater the magnitude of shock received or transmitted.

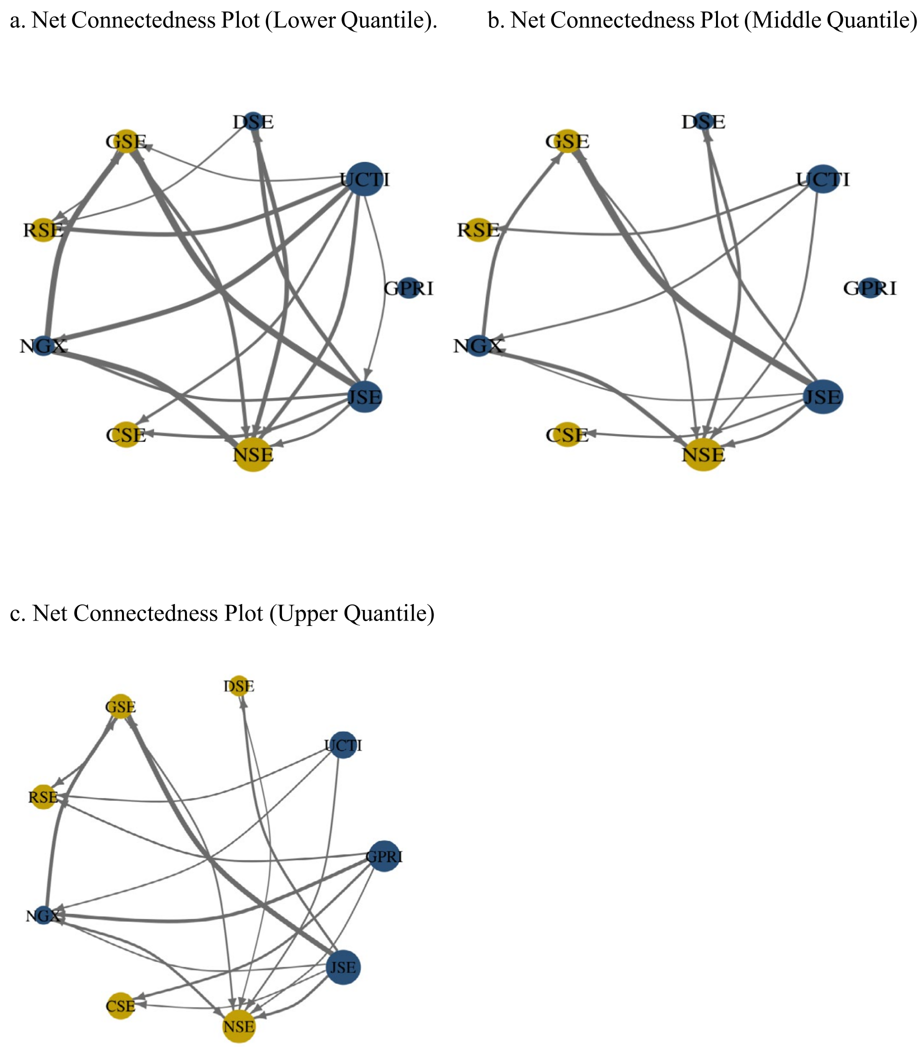

Fig. 3 Returns Connectedness Network Plot. Source: Authors' own work

Robustness analysis

To ensure the credibility of our findings and address potential concerns regarding model specification, outlier-driven results, and endogeneity, we conducted a series of robustness checks. Endogeneity, potentially arising from reverse causality or omitted variable bias, is a common concern in financial spillover studies. For instance, while we posit that U.S.–China tensions affect African markets, a severe downturn in a systemically important African market could, in theory, influence global risk perceptions. Our time–frequency and quantile-based approaches inherently mitigate this by modeling asymmetries and lead-lag relationships. The following tests further bolster the confidence in our conclusions.

Alternative lage structures in the QVAR model

The baseline QVAR model was estimated with a lag length of 2, selected by the Akaike Information Criterion (AIC). To test for sensitivity, we re-estimated the model using lag orders of 1 and 3. The results were qualitatively unchanged. The identity of the key net transmitters (UCTI, GPRI, JSE) and net receivers (NGX, NSE) remained consistent across lag specifications. While the absolute magnitude of the spillover indices varied slightly, the core finding of state-dependent vulnerability-and the regime-specific dominance of UCTI versus GPRI held robustly. This indicates that the documented connectedness topology is not an artifact of an arbitrary lag selection.

Sensitivity to alternative quantile choices

Our main analysis focused on the lower ($\tau = 0.05$), median ($\tau = 0.50$), and upper ($\tau = 0.95$) quantiles to capture bearish, normal, and bullish regimes. We expanded this to include intermediate quantiles ($\tau = 0.10$, 0.25, 0.75, 0.90) to create a more continuous view of regime dependence. The results from this expanded analysis confirm a smooth transition in spillover dynamics. The dominance of UCTI is most pronounced in the lower quantiles ($\tau = 0.10$, 0.25), progressively gives way to a more balanced influence around the median, and is unequivocally superseded by GPRI in the upper quantiles ($\tau = 0.75$, 0.90). This gradient effect strongly reinforces our hypothesis that the primary source of risk is not static but evolves with the market state.

Sub-sample analysis excluding the COVID-19 period

The period from March 2020 to late 2021 represents an extreme global shock that could disproportionately drive our results. To verify that our findings are not solely a pandemic-era phenomenon, we re-ran the QVAR analysis on a subsample ending in December 2019. The core results remain intact: UCTI remained the dominant net transmitter in calm (lower quantile) markets; GPRI's role as a key shock transmitter during periods of stress was still evident, driven by pre-pandemic events such as the 2018–2019 trade war escalations and earlier geopolitical crises; the JSE's role as a net transmitter and the NGX's as a net receiver were, if anything, even more pronounced, suggesting these roles are structural and not crisis-dependent.

This confirms that the documented vulnerabilities are fundamental characteristics of the interconnectedness between African markets and global shocks, rather than an artifact of the COVID-19 shock.

Conclusion

This study demonstrates that the vulnerability of African stock markets to U.S.–China trade tensions and geopolitical risks is not static but is profoundly time-dependent and regime-specific. The wavelet coherence analysis reveals that the influence of these global shocks clusters around major events, with pronounced co-movement occurring at medium-to-long-term horizons (8–32 months) during critical periods such as the 2018–2019 tariff escalations, the COVID-19 pandemic, and the 2022 technology restrictions. This time–frequency dynamic shows that African markets, while not initiating these shocks, consistently react with a lag, as indicated by the dominant down-right phase arrows. Complementing this, the QVAR analysis confirms that the dominance of these shocks is regime-driven: trade-policy uncertainty prevails in calm periods, both factors matter in normal conditions, and geopolitical risk becomes paramount during crises. Thus, African markets are far from immune; their integration into the global financial system makes them susceptible to external uncertainties in a way that is dynamically shaped by both the timing and the severity of the shock.

Implications of the study

The findings carry significant implications for policymakers, investors, and financial institutions. Policymakers should prioritize enhancing regional financial integration and strengthening domestic regulatory frameworks to mitigate spillover effects from global uncertainties. Investors can use these insights to identify markets with higher resilience, such as South Africa, and adjust their portfolios based on the prevailing global risk regime. For financial stability, central banks and market regulators should develop countercyclical policies and early-warning systems that account for the asymmetric and regime-specific nature of external shocks, particularly those originating from trade and geopolitical conflicts.

Limitations

This study is subject to several limitations. First, the reliance on monthly data may obscure higher-frequency dynamics and immediate market reactions to sudden geopolitical or trade events. Second, the selection of seven major African exchanges, while representative of most of the continent's market capitalization, may not fully capture the behavior of smaller or less formalized markets. Third, the constructed indices (GPRI and UCTI) are based on English-language media sources, which might underrepresent regional or non-Western perspectives on geopolitical and trade tensions.

Recommendations for future studies

Future research could extend this work by incorporating high-frequency data to capture intraday or weekly market reactions, thus providing more granular insights into shock transmission. Expanding the sample to include more African exchanges, especially from Francophone regions, would improve the continental representativeness of findings. Additionally, developing region-specific geopolitical risk indices that reflect local media and political contexts could offer a more nuanced understanding of risk perceptions. Finally, applying similar methodologies to other emerging markets or comparing African responses with those in Latin America or Asia could help contextualize the continent's unique position within the global financial system.

Data availbility

Data is available upon reasonable request.

Author contribution
DK prepared the first three sections of this manuscript, while SKD prepared the last two sections of the paper (Findings and Discussion, and the Conclusion Section).

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