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The impact of geopolitical risks, financial stress, economic policy uncertainty on African stock markets returns and volatilities: wavelet coherence analysis

David Korsah, Godfred Amewu and Kofi Osei Achampong
University of Ghana, Accra, Ghana

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Abstract

Purpose – This study seeks to examine the relationship between macroeconomic shock indicators, namely geopolitical risk (GPR), global economic policy uncertainty (GEPU) and financial stress (FS), and returns as well as volatilities on seven carefully selected stock markets in Africa. Specifically, the study intends to unravel the co-movement and interdependence between the respective macroeconomic shock indicators and each of the stock markets under consideration across time and frequency.

Design/methodology/approach – This study employed wavelet coherence approach to examine the strength and stability of the relationships across different time scales and frequency components, thereby providing valuable insights into specific periods and frequency ranges where the relationships are particularly pronounced.

Findings – The study found that GEPU, Financial Stress (FS) and GPR failed to induce significant influence on African stock market returns in the short term (0–4 months band), but tend to intensify in the long-term band (after 6th month). On the contrary, stock market volatilities exhibited strong coherence and interdependence with GEPU, FSI and GPR in the short-term band.

Originality/value – This study happens to be the first of its kind to comprehensively consider how the aforementioned macro-economic shock indicators impact stock markets returns and volatilities over time and frequency. Further, none of the earlier studies has attempted to examine the relationship between macro-economic shocks, stock returns and volatilities in different crisis periods. This study is the first of its kind in to

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All authors reviewed the results, approved the final version of the manuscript and all authors agree to be accountable for all aspects of the work.

Disclosure of interest: There is no interest to declare.

Data availability statement: The data for the stock market are in monthly frequency and were gleaned from Bloomberg.

The macroeconomic shock indexes, namely GPR, FS, and GEPU, were sourced from http://policyuncertainty.com

The dataset for this study would be made available upon request.

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employ data spanning from May 2007 to April 2023, thereby covering notable crisis periods such as global financial crisis (GFC) and the COVID-19 pandemic episodes.

Keywords Economic policy uncertainty, Geopolitical risk, Financial stress, Wavelet coherence analysis

Paper type Research paper

1. Introduction

The African stock markets (ASMs) have recorded significant growth over the years, marked by a sharp rise in the number of stock markets from two (2) in 1990 to twenty-nine (29) as of 2022 (Ehiedu and Obi, 2022), and an upward trend in the stocks traded turnover ratio from 9.29% in 1993 to 31.54% by the close of 2019. The contemporary growth and transformation of ASMs, spurred by financial reforms and increased listings, signify the markets' growing importance within the global financial landscape (Akinlo and Egbetunde, 2010).

Despite the strides made over the years, majority of ASMs are still at the nascent stage, rendering them highly susceptible to both internal and externals shocks. Notable events like the global financial crisis (GFC) and COVID-19 pandemic, which resulted in substantial declines in stock prices, heightened market volatility, and liquidity constraints (Zoungrana *et al.*, 2023; Takyi and Bentum-Ennin, 2021), have largely exposed the vulnerability of African markets to shocks.

Das *et al.* (2019) established that shocks to stock markets could be traced to three critical macroeconomic indicators, namely geopolitical risks (GPRs), GEPU and financial stress (FS). Regrettably, there is dearth of literature on GPR, GEPU, FS and stock market nexus, a situation that has been attributed to the absence of a quantitative, reliable and continuous measure of the aforesaid shock indicators. Meanwhile, the development of GPR index by Caldara and Iacoviello (2021), EPU index by Baker *et al.* (2016), and FS index have been crucial in remedying the challenge (Das *et al.*, 2019).

GPRs, broadly defined as risks associated with wars, terrorist acts and tensions between states, affecting normal course of domestic politics and international relations (Caldara and Iacoviello, 2021), unarguably trigger wild swings in the global economy, particularly financial markets (Chiang, 2021; Elsayed and Helmi, 2021). Equally, GEPU, characterized by skepticisms in future dealings of government-induced policies, notably fiscal, monetary and regulatory policies amidst economic turmoil, invariably compels individuals and firms to suspend investment, production and spending decisions (Mehrdoust and Samimi, 2020), culminating into heightened stock market volatilities. Similarly, the impact of FS, an index for measuring the stress level of financial system, and assessing the depth and duration of instability of financial markets and the efficiency of anti-crisis measures, on returns on stock markets cannot be overemphasized (Su *et al.*, 2019).

Worryingly, to the best of our knowledge, none of the earlier studies has comprehensively considered how the aforementioned macro-economic shocks indicators impact stock markets returns and volatilities over time and frequency, particularly in the African context. Studies that attempted to examine the relationship between stock returns and macroeconomic shocks focused mainly on EPU-stock market nexus (Arouri *et al.*, 2016; Asafo-Adjei *et al.*, 2020). A study by Korsah and Mensah (2023) which examined macroeconomic shocks and stock market relationship only concentrated on stock returns, and the extent of connectedness and spillovers but failed to consider volatilities as well as time and frequency dynamics of the ASMs and the macroeconomic shock indicators under consideration. Another critical shortcoming of earlier studies is the failure to capture the relationship between the said macro-economic shock indicators and stock returns/volatilities in different crisis periods.

This study seeks to examine the relationship between GPR, GEPU and FS, and returns/volatilities on seven (7) carefully selected stock markets in Africa, paying critical attention to the extent of co-movement and interdependence in crisis episodes. Findings of this study would provide quintessential information on successful portfolio diversification, as investors could rely on same to make informed decisions on the timings of their investments. Additionally, the findings would help policy makers to ascertain impact of the macroeconomic shocks on returns on the stock market, and their respective economies at large, to make informed policy decisions to avert or mitigate the negative repercussions.

2. Literature review

2.1 Theoretical review

This study hinges on two seemingly conflicting theories, that is decoupling theory and financial network theory. Decoupling hypothesis posits that emerging economies have a limited connection to advanced countries' financial markets. Proponents of this theory argue that emerging markets can insulate themselves from global crises by implementing policies that create structural breaks in interconnectedness. Notable studies by Dooley and Hutchison (2009), Boako and Alagidede (2016) support this view, highlighting the apparent immunity of emerging markets to shocks from advanced economies.

On the contrary, critics, such as Balcilar and Demirer (2015) suggest that emerging markets, especially in Africa, cannot completely shield themselves from global shocks, challenging the reliability of the decoupling theory. This is in line with the assumptions underpinning financial network theory. Broadly, the financial network theory highlights the intricate interactions and dependencies among financial institutions and markets. The theory postulates that the financial landscape is characterized by scale-free networks and highly connected nodes, thereby propelling shock transmissions and contagion spread (Allen and Babus, 2009; Caldarelli, 2007). To put in proper perspective, while decoupling hypothesis suggests a limited connection between emerging and advanced economies' financial markets, financial network theory emphasizes understanding the complex interdependencies within financial ecosystem to manage risks effectively.

2.2 Emperical literical review

As has already been espoused, GPRs are war-like events that have the potential to trigger uncertainties in the market. Interest in this area of study intensified following the development of an index for GPRs by Caldara and Iacoviello (2018). The GPR index has been widely employed by researchers because it encapsulates different geopolitical issues (Drakos, 2010; Kollias *et al.*, 2011), and their accompanying risky events. Subsequently, extant literature has attempted to examine the impact of GPRs on assets, notably oil (Bouoiyour *et al.*, 2019), commodities (Ramiah *et al.*, 2010) and precious metals (Baur and Smales, 2020). Other strand of literature has also focused on the predictive capacity of GPRs in forecasting possible changes in stock prices, bitcoin returns (Bouri and Gupta, 2021), among others. Suffice to say that findings in literature are largely dependent on the country, region and sector of the economy, and the nature of GPR event under consideration. For instance, the tourism sector is deemed as one of the most sensitive sectors to GPRs. This has been confirmed by Akadiri *et al.* (2020), observing that high GPRs undermine tourism-related economic activities.

On the GPRs and stock market returns front, Balcilar *et al.* (2017) found a significant and negative relationship between GPRs and stock market returns and volatility in G7 nations, with Japan and UK being the most vulnerable markets. For Brazil, Russia, India, China and South Africa (BRICS), Balcilar *et al.* (2018) used nonparametric causality-in-quantile tests to examine the impact of GPRs on stock returns and volatility. The study discovered that GPRs have a stronger influence on stock market volatility than on stock market returns. A similar study by Rawat and Arif (2018), employing a quantile regression on a data spanning 1985–

2017, found that, among the BRICS nations, the Indian and Chinese stock markets were the most resilient to GPRs, while Brazilian and Russian stock markets were found to be most vulnerable. The researchers conclude that China and India may provide investors with a safe haven. Considering the time-frequency dynamics of GPRs and stock returns in 14 developing nations, Sekmen (2020) found that the impact of GPRs on stock returns heightens substantially in times of escalating geopolitical threats. Smales (2021) in a related study attempted to examine the relationship between GPRs, and returns and volatility on the US market. The researcher observed a weak connection between stock returns and GPRs, after employing both univariate and multivariate Generalized autoregression conditional heteroskedasticity (GARCH) models. Das *et al.* (2019) investigated the heterogeneity of the impact of GPRs on stock market returns and volatilities, and concluded that the effect of GPRs on stock market returns is more pronounced in developing countries.

GEPU has equally become a key determinant of investment decisions, economic cycles and policy formulations, especially in the aftermath of the GFC. Fittingly, research interest in this area, particularly reaction of stock prices to changes in GEPU, has deepened in recent years. Notable among them is a study by Sum (2012), which delved into GEPU and stock market performance in Asia from 1985 to 2012. The study established that high GEPU lowers stock market returns in 5 ASEAN nations, and underscored that there is a direct link between EPU and stock market returns in Singapore and Malaysia. Pástor and Veronesi (2013) postulate that although GEPU mostly has dire ramifications, it can have a positive impact on stock returns if authorities in affected countries are able to roll out pragmatic measures to absorb the shocks. Similarly, Liu and Zhang (2015), sourcing data from the S&P 500 between 1996 and 2013, observe a negative relationship between GEPU and stock returns. In the OECD nations, Asteriou and Sarantidis' (2016) revealed GEPU had a negative impact on stock market returns, and this effect was more pronounced in the banking sector stocks. In the US stock market, between 1985 and 2014, Baker *et al.* (2016) found that EPU propels volatility in stock prices. Phan *et al.* (2018) postulate that there exists a heterogeneous relationship between GEPU and stock returns across markets and regions. A study by Asafo-Adjei *et al.* (2020), one of the few studies in the context of Africa, used wavelet coherence analysis on daily data sourced from eight (8) African markets, spanning from December 2010 to December 2019, to examine EPU-and stock returns co-movement. The results showed GEPU co-move with stock market returns, at least in the long term, and concluded stock markets in Africa is a viable avenue for hedging against policy uncertainties, especially in the short to medium term.

The GFC crisis brought to bear the dire repercussions of stress in the financial sector on other sectors. The event underscored the need for an up-to-speed and accurate signals of FS to inform mitigating measures. Carlson *et al.* (2014) define FS as being directly related to functioning of the financial market, while Louzis and Vouldis (2013) briefly define FS as "systemic risk which has materialized". Grimaldi (2011) describe FS as the outcome of "interactions between vulnerabilities in markets and shocks." Research in this area has focused on the construction of FS indexes for a country or a group of countries (Vermeulen *et al.*, 2015; Cevik *et al.*, 2016). Mallick and Sousa (2013) observed that FS significantly impact commodity prices, gross domestic product (GDP), interest rates and economic growth. The dearth of literature on FS and stock market nexus, with notable exception by Sum (2012), Das *et al.* (2019) and Wang and You (2022) which found a negative relationship between FS and stock market returns, makes this research more plausible.

As has been espoused, empirical literature reviewed have revealed that the extent of sensitivity of markets to macro-economic shocks differ across countries and regions. Clearly, findings in developed markets, which have been the main focus of earlier studies, can not necessarily be applied in Emerging Markets, particularly Africa.

From the foregoing, it is fair to conclude that there exists divergent finding on the impact of GPR, FS and EPU on stock markets across the globe. While some studies have established positive relationship, extant literature has recorded negative association between the respective macroeconomic shock index and stock markets. Other strand of literature also asserts that the relationship between the indexes and stocks returns and volatilities is market specific. This long-standing bone of contention, coupled with the lack of extensive studies in the context of the ASM make this study very critical. A priori, we expect a strong relationship between the variables under consideration and stock market returns and volatilities in Africa.

3. Data and methodology

3.1 Data

The study makes use of seven (7) exchanges from Africa, where at least one stock exchange is selected from each of the five geographical zones namely, North Africa, South Africa, East Africa, West African and Central Africa in order to get a fair representation from the continent. The Egyptian exchange (EGX) (Egypt) and the Bourse de Casablanca (Morocco) represent the North African region; whilst Johannesburg stock exchange (JSE) (South Africa) represents the southern part of Africa. In East Africa, Nairobi securities exchange (Kenya) and Dar es Salaam stock exchange (Tanzania) were used as proxies, whiles the Ghana stock exchange (GSE) (Ghana) and the Nigeria stock exchange represent the West of Africa.

Further, the equity markets were selected on the basis of their respective market capitalization. Data from CEIC website indicate that, as of July 2023, combined capitalization of 29 stock exchanges in Africa amounted to US$1.6 trillion. The total capitalization of JSE, Nigerian exchange (NGX), Casablanca stock exchange (CSE), Egyptian exchange, Nairobi stock exchange (NSE), GSE and De Saar stock exchange (DSE) totaled US$1.356tn, US$45.9bn, US$63.6bn, US$31.2bn, US$11.54bn, US$6.550bn and US$6.2bn, respectively. Cumulatively, this constitutes 95% of the total market capitalization of stock markets in Africa. The data for the stock market are in monthly frequency, are gleaned from Bloomberg.

The macroeconomic shock indexes, namely GPR, FS and GEPU are sourced from http://policyuncertainty.com, spanning from May 2007 to April 2023, with a monthly frequency. GPR index 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. GEPU captures actual and anticipated changes in government policies. The higher the index, the greater the level of uncertainty. FS, developed by Püttmann (2018), is constructed from five (5) US-based newspapers, focusing primarily on words related to “bonds”, “stocks”, “business”, “central banks”, “trade” and “inflation”. The selected indexes are intertwined factors that collectively and significantly influence the ASM, inducing investor sentiment, market volatility, foreign investment, among others. Thus, understanding their respective effects on stock market returns is crucial for informed policy and investment decisions.

3.2 Methodology

3.2.1 Bivariate wavelet coherence. In line with the primary objective of this study, i.e. examining time frequency dynamics of stock market returns and macro-economic shocks, we employ bivariate wavelet method. Wavelet is defined as a small wave which has the potential to stretch overtime to bring to bear frequency components from complex signals (Amewu *et al.*, 2022). The bivariate wavelet method is selected owing to its ability to provide in-depth appreciation of interlinkages that stem from either market fundamentals or transitory (Ftiti *et al.*, 2016). Additionally, this approach requires no prior-treatment of time series data to be employed, decomposes data into different time-frequency domains, thus safeguarding against the loss of vital information and irregularities in data structure. Further, the model presents analysts with insight into whether time series data (market) exhibit short, medium or long-term interlinkages through its graphical features. In essence, the application of this model in this study may offer investors an opportunity to assess the connectedness and the co-movement of macroeconomic shocks and volatilities on the stock market, thus informing investment decisions.

3.2.2 Continuous wavelet transform. There are two basic categories of wavelet transforms: the continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT). Madaleno 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 macroeconomic 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 (Grinsted *et al.*, 2004). 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 (Grinsted *et al.*, 2004; Rua and Nunes, 2009).

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 (WPS) and phase difference.

According to Ng and Chan (2012), 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 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 (Vacha and Barunik, 2012), 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 WPS. In line with Torrence and Webster (1999), the squared wavelet co-efficient is expressed as follows:

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

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 color. 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 WPS and wavelet cross-spectrum is eliminated by the normalizing function of the wavelet coherence.

3.2.3 Wavelet Transform Coherence (WTC) phase difference. The WTC phase difference indicates the interruptions in the oscillation concerning the examined time series. Following Bloomfield *et al.* (2004), the phase difference between $x(t)$ and $y(t)$ is represented as follows:

$$\varnothing_{xy}(i,s) = tan^{-1}\left(\frac{I\{S(s^{-1}W_{xy}(i,s))\}}{R\{S(s^{-1}W_{xy}(i,s))\}}\right) \varnothing_{xy}(i,s) \in [-\pi,\pi] \tag{6}$$

where I and R 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 ($\rightarrow$ and left-pointing arrows ($\leftarrow$) 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 ($\nearrow$) and left arrows pointing downward ($\swarrow$) indicate that the first variable is lagging. Conversely, left arrows pointing upward ($\nwarrow$) and right arrows pointing downward ($\searrow$) depict that the first variable is leading.

3.2.4 Econometric model. In achieving the primary objective of the study, we computed the continuous compounding returns for the respective markets by estimating the log returns as follows:

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

where R_t denote the monthly market returns, P_t and P_{t-1} represent the current price and previous month's price, respectively.

We further computed monthly market volatility from GARCH (1,1) model developed by Engle and Bollerslev (1986), expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \sum \varepsilon_{t-i}^2 + \alpha_2 \sum \sigma_{t-i}^2 \tag{8}$$

where σ_t^2 is the conditional variance, α_0 is the constant term, ε_{t-i}^2 (ARCH term) denotes the volatility from the previous month, which is estimated as a lag of squared residual from the mean equation. Finally, σ_{t-i}^2 (GARCH term) represents the last period forecast variance.

The GARCH model is employed in this study given its unique capability to capture irregular pattern of variation of error term, thus making it a more robust model.

4. Results and discussion

4.1 Descriptive statistics

Table 1 presents the summary of the returns series of the stock markets under consideration, and the macroeconomic shock indicators (proxies), notably GPR, GEPU and FS indicator. The statistics comprise the mean, median, maximum return, minimum returns, standard deviation (Std. Dev), skewness, kurtosis and observations (obs.).

It is observed that the variables under consideration have the same number of observations, i.e. 191. The mean of the returns for almost all the stock markets is 0, with the exception of Kenya and South Africa which recorded −0.01 and 1, respectively (Table 1). It can therefore be deduced that, on the average, the JSE provides the highest monthly returns for the period under consideration – from April 2017 to March 2023. Further, it can be observed that, on the average, returns of NSE, represented by NSE, is the least among the markets under consideration, depicted by mean of −0.01 (Table 1).

Additionally, the maximum monthly returns for the market for the period under consideration was recorded by JSE, Nigeria stock exchange (NGX) and EGX, realizing 123, 32 and 29% returns, respectively (Table 1). From Table 1, the highest monthly returns on the CSE was 10%, the least of the maximum returns in the Africa markets considered. The GSE, among the various markets, suffered the heaviest loss within the period, in March 2011, with monthly log minimum return of −0.54.

The standard deviation (Std) figures from Table 1 reveal the risk levels of the respective markets. It can be observed that the GSE is the riskiest of all the markets, with an average monthly volatility of 15%. This is followed, closely, by EGX (9%), and NGX (7%). DSE is the least risky market in Africa, with average monthly volatility of 3% (Table 1).

The skewness and kurtosis depict the shape and pattern of the monthly returns (Table 1). It can be observed that the monthly returns for all the markets are negatively skewed. This implies investors are more likely to suffer losses in the markets. The kurtosis figures for the markets, with the exception of EGX (2.31) and JSE (1.98), are above 3, signaling that the distributions of the returns' series are leptokurtic (fatter tails).

4.2 Wavelet coherence analysis

The findings of the wavelet approach are presented in Figures 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/volatilities. The extent of interdependence between the series is determined by the color of the surface. Warmer colors (red) depict high correlation whereas cold colors (blue) indicate 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.

4.2.1 Discussion of results. From Figure 1(a), it can be observed that, generally, there exists a weak coherence between GEPU and stock market returns in the short-term (0–4 months band). A careful observation of Figure 1(a) reveals that coherence intensifies with time. Considering GSE and GEPU, the coherence was weak amidst the GFC (between 2007 and 2009), at least in the short term. The coherence tends to increase in the long term, after 15th month, with right arrow pointing downwards signifying that GSE is leading. Between 2009 and 2017, it can be observed that GSE and GEPU are weakly correlated, except from 2012 to 2013, where GSE is lagging. Again, there is evidence of strong interrelation in the medium term (15th to 30th month band) from 2014 to 2022. The left-pointing downwards arrows indicate that the GSE is lagging (Figure 1(a)). It is noteworthy that the change in the directions of the arrow reveals a cyclical interaction between the pair, consistent with Asafo-Adjei *et al.* (2020).

Table 1. Descriptive statistics for log stock returns and macroeconomic shocks

		Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	Obs
Africa equity markets									
Morocco	CSE	0.0000	0.0000	0.1000	−0.2300	0.0400	−1.0400	5.9000	191
Egypt	EGX	0.0000	0.0100	0.2900	−0.3900	0.0900	−0.5000	2.3100	191
South Africa	JSE	0.5000	0.5000	1.2300	−0.0700	0.0800	−0.2900	1.9800	191
Kenya	NSE	−0.0100	0.0000	0.1600	−0.3200	0.0600	−1.1800	5.9400	191
Nigeria	NGX	0.0000	0.0000	0.3200	−0.3700	0.0700	−0.3200	4.6000	191
Tanzania	DSE	0.0000	0.0000	0.1300	−0.1500	0.0300	−0.3500	4.6800	191
Ghana	GSE	0.0000	0.0100	0.1800	−0.5400	0.1500	−1.7500	13.8700	191
Macro-economic shock indicators									
Geopolitical risk	GPR	0.0200	−0.006	0.8630	−0.4510	0.2030	1.0920	5.4960	191
Economic policy uncertainty	GEPU	0.0270	−0.004	0.8690	−0.3900	0.2050	1.3840	6.4750	191
Financial stress	FS	−0.5190	−0.110	16.1480	−15.1480	3.0240	0.3460	15.0390	191

Source(s): Authors' construction

Similarly, from Figure 1(a), we noticed few small islands of red contours between the 0-month and 8-months band between GEPU and CSE, JSE, EGX, NSE and DSE across the years under consideration. From plots in Figure 1(a), we observe that the NGX exhibit the weakest coherence with GEPU, at least in the short term, supporting the findings of Ogbuabor *et al.* (2021). This suggests that the NGX is somewhat immune to economic policy uncertainty in the short term. However, investors who hold their investments in the said markets beyond

(a) Stock Market Returns and GEPU

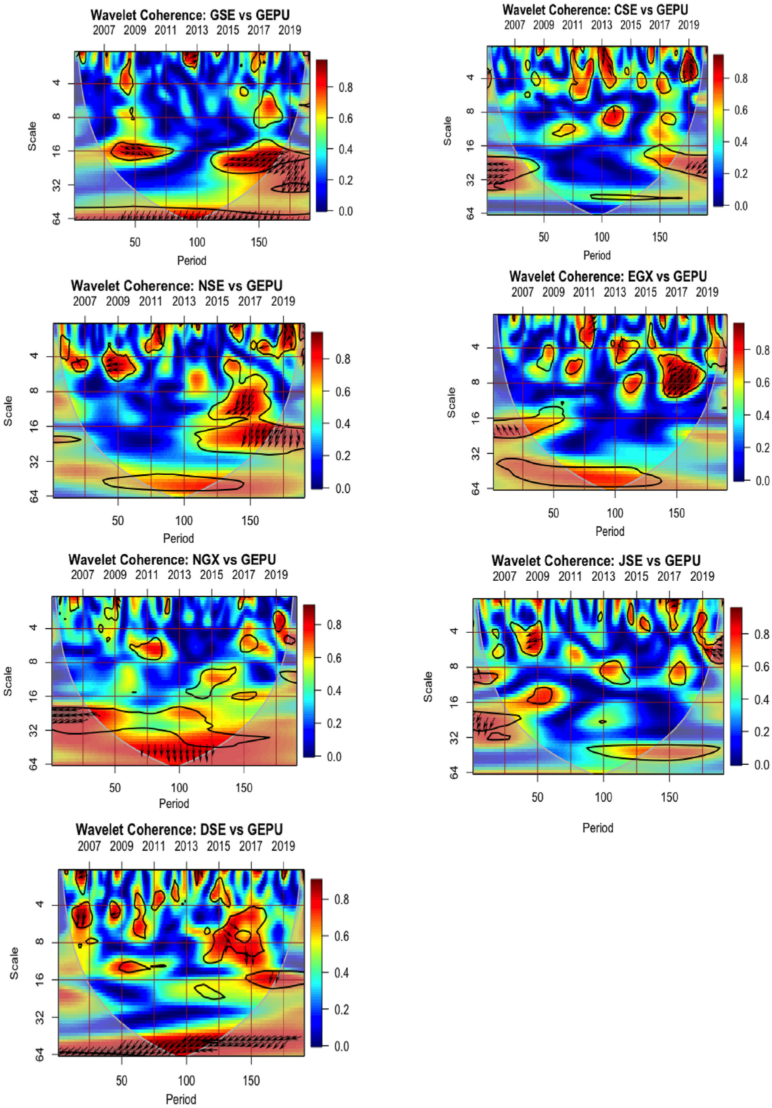


Figure 1.
Stock returns and macroeconomic shocks nexus

(*continued*)

(b) Stock Market Returns and FSI

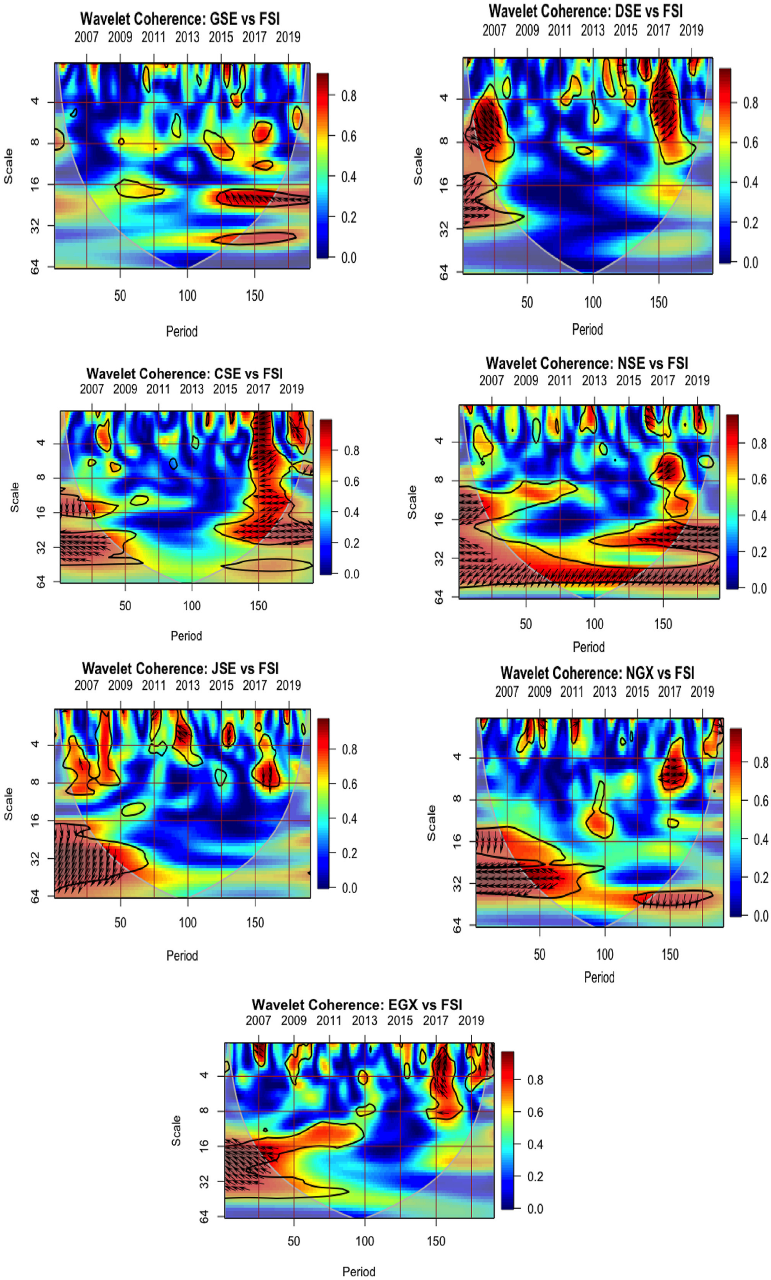


Figure 1.
(*continued*)

(c) Stock Market Returns and GPR

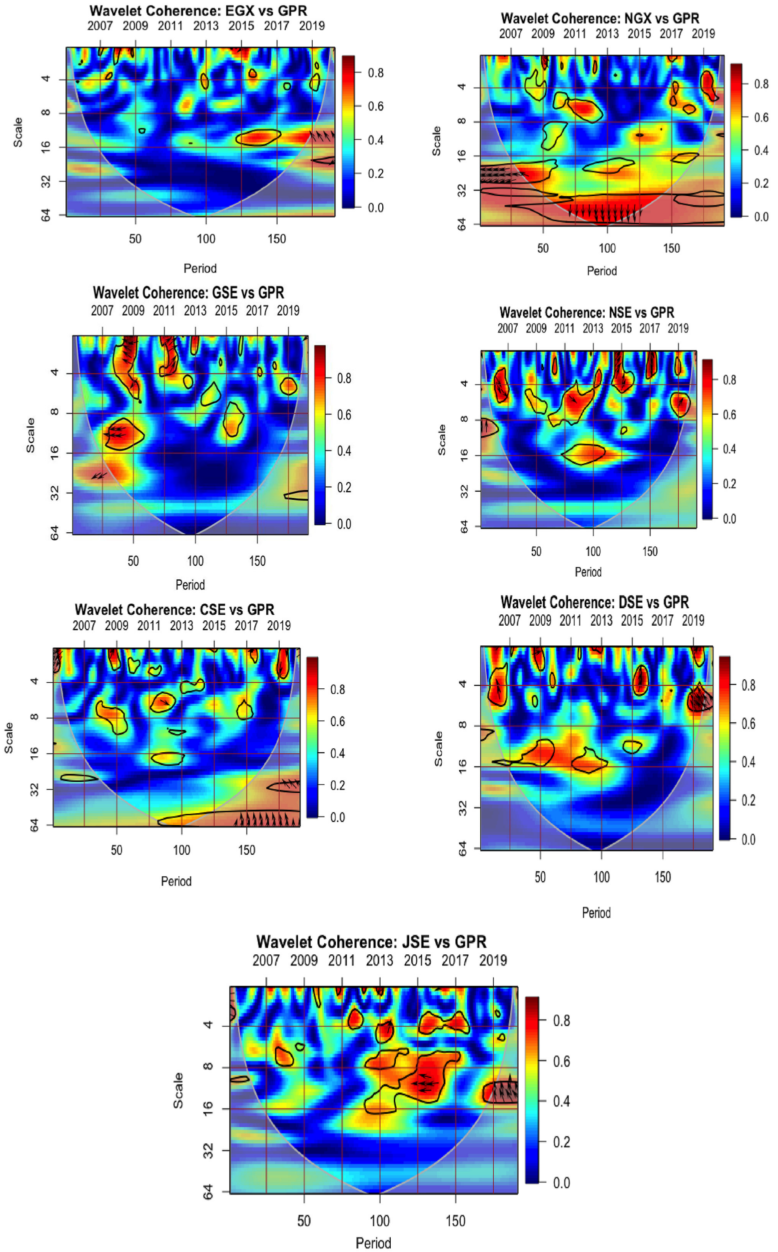


Figure 1.

Source(s): Figure by authors

(a) Stock Market Volatilities and Geopolitical Risk

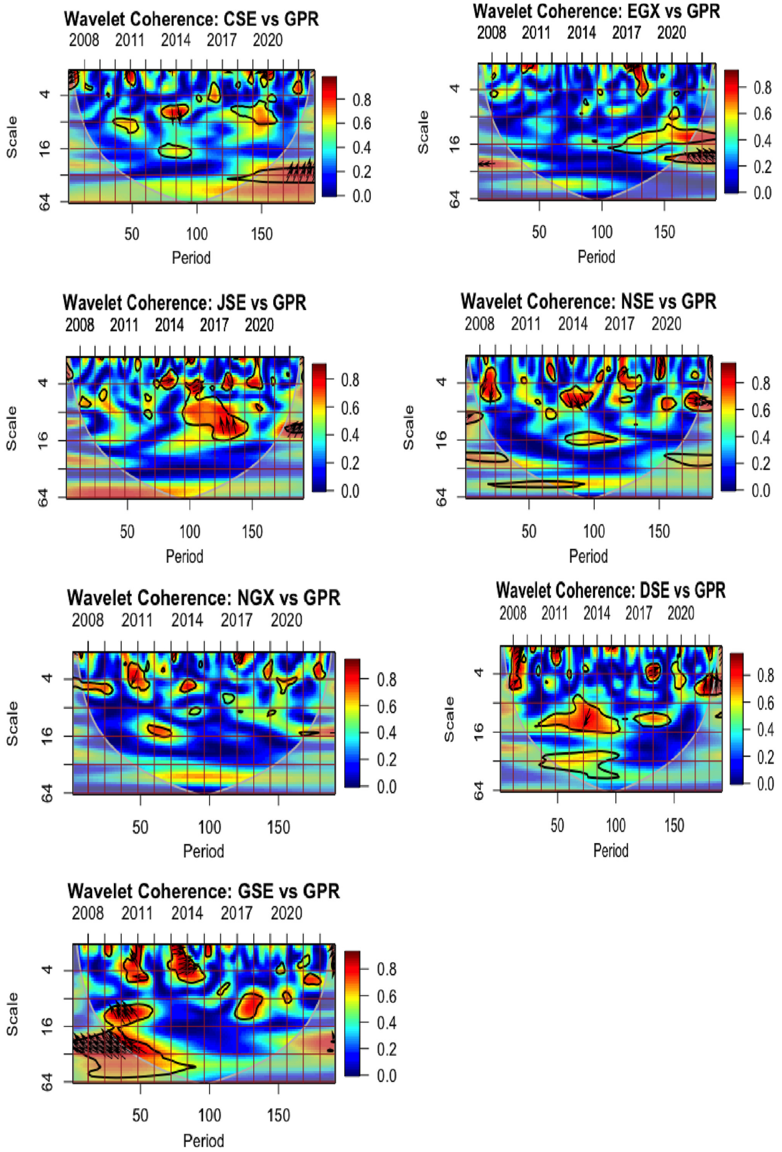


Figure 2.
Stock volatilities and macroeconomic shocks nexus

(*continued*)

(b) Stock Market Volatilities Economic Policy Uncertainty

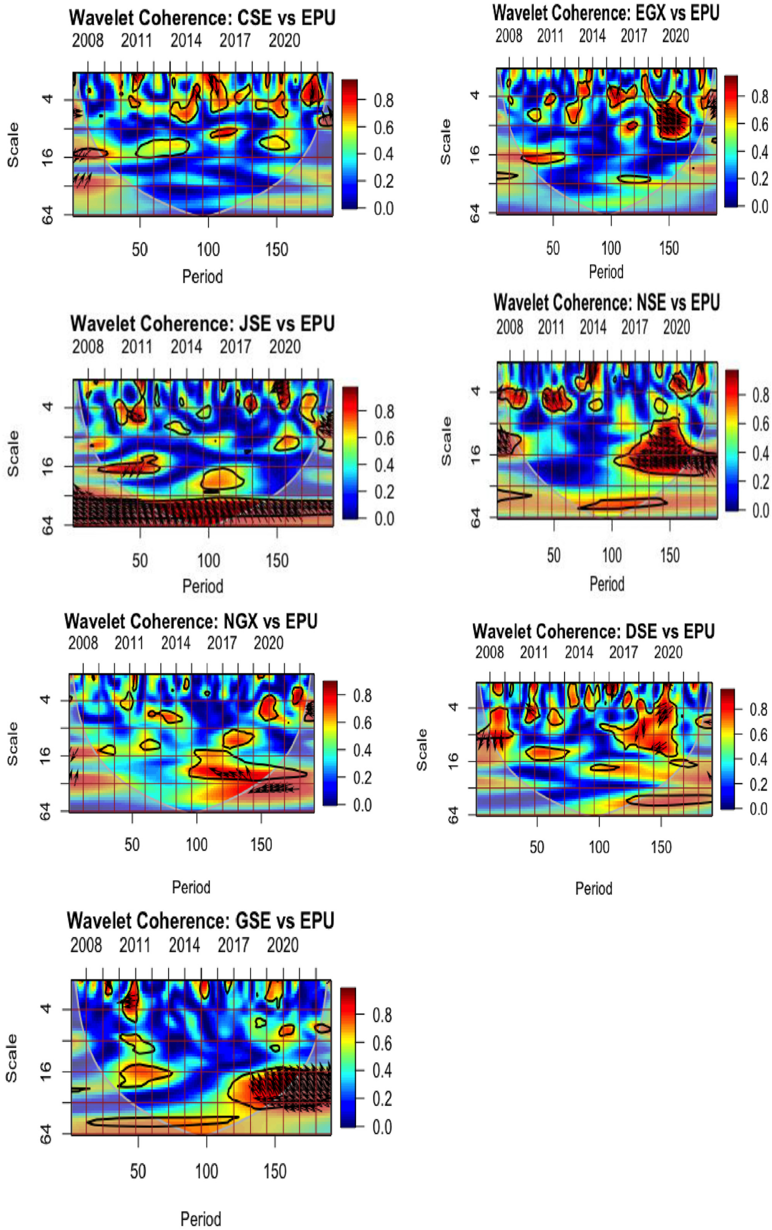
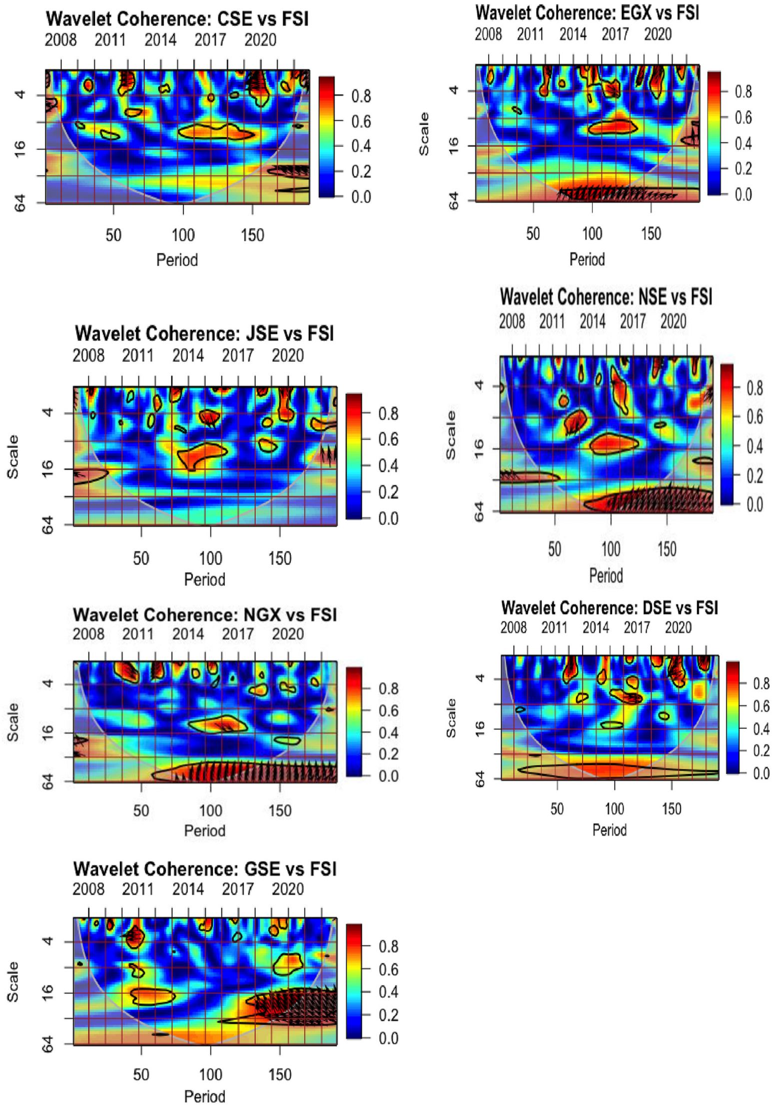


Figure 2.

(*continued*)

(c) Stock Market Volatilities and Financial Stress



Source(s): Figure by authors

Figure 2.

four (4) months are likely to suffer the ramifications of GEPU, consistent with a study by Asafo-Adjei *et al.* (2020) which concluded that the co-movement between stock returns in Africa and economic policy uncertainty are more pronounced in the long term.

Figure 1(b) presents the coherence between FSI and stock market returns. A case-by-case examination of the plot reveals that coherence between FSI and returns on stock markets intensify in the medium to long term. In the case of GSE, we observe small islands of contours, particularly between 2015 and 2016, demonstrating interrelation between the pairs, although weak (Figure 1(b)). The momentum of the coherence became stronger in the medium to long term, after 2015. Clearly, the interrelation between the GSE and FSI is generally faint in the short term.

Focusing on the coherence between FSI and EGX, the plot reveals strong correlation in 2007–2008, amidst the GFC, in the short term, with left-downward pointing arrows depicting that FSI is lagging (Figure 1(b)). The plot recorded little to no co-movement between the pairs until after 2017, where there appeared to be strong coherence in both the short term (0–4 months band) and medium term (4–8 months band). Regarding the JSE, there is evidence of coherence between FSI and returns on the JSE in the short-term band, especially between 2007 and 2009, 2011 and 2013, and 2015 (Figure 1(b)). It could be inferred that investors on the JSE are likely to be affected by shocks emanating from FSI within the first four (4) months of occurrence. From Figure 1(b), Just like the JSE, the NSE, CSE, NGX and DSE exhibit similar coherence with FSI. In all the plots for the respective markets and FSI, it can be observed that there is weak coherence in the short-term. Another observation is that the magnitude of co-movement between FSI and stock market returns deepens from 2015 for most of the markets, especially the JSE, NSE, CSE and DSE, bringing to the fore the significance of recent spate of globalization on shock propagation (Figure 1). In all, it is fair to infer that FSI and stock market returns exhibit strong coherence in the medium to long term, in line with Das *et al.* (2019).

On the GPR-stock market returns coherence front, shown in Figure 1(c) below, a careful observation reveals that the interdependency between the GPR and returns on the respective stock market is generally weak. Typically, NGX, CSE and EGX portray feeble relations with GPR, at least in the short-term. The coherence between stock market returns and GPR is more pronounced on the GSE, from 2008 to 2012, and the JSE and DSE, in the short term, across the period under consideration (Figure 1(c)). Similar to the interrelation between stock market returns, and GEPU and FSI, the magnitude of coherence between GPR and stock returns deepen in the medium to long term. Further, the contours of red islands in the COI reveals that JSE and NSE are tend to have a relatively stronger relationship with GPR. This implies that investments in the said markets are quite susceptible to GPR shocks.

It is evident from the various plots in Figure 1 that GEPU, FSI and GPR do not exert significant influence on ASMs in the short term, that is 0–4 months band, signified by the weak coherence. However, the coherence strengthens in the medium to long term. This suggests that shocks in GEPU, FSI and GPR may not be robust to determine variations in returns on ASM in the short term, thus presenting the ASM as an ideal investment destination for investors who intend to hedge against global uncertainties in the short-term.

From the foregoing, it is clear that returns on the ASMs are not significantly influenced by GPRs, FS, or economic policy uncertainty, at least in the short term. This implies that investors in African stocks may not react strongly to immediate changes in these factors when making short-term investment decisions.

Further, this study delves into the relationship between the volatilities of respective stock markets and macro-economic economic shock indicators under consideration. This is crucial given that volatility on the stock market largely serves as an early warning sign (Wang *et al.*, 2020), and that a better appreciation of same is vital for risk management and investment decisions (Bhowmik and Wang, 2020).

The findings are displayed in Figure 2. We begin with stock market volatilities and GPR nexus. A careful observation of the plots in Figure 2(a) reveals that there exists a strong relationship between GPR and ASMs in the short term (0–4 months band). For instance, the CSE, EGX, Nigerian stock exchange (NGX) and the GSE, suggest that the intensity of the coherence is more pronounced in the short term (Figure 2(a)). Although same cannot be said of the Johannesburg stock exchange (JSE), Dar es Salaam exchange (DES), there are evidence of red contours in the short-term band. It can be inferred from the findings that, volatilities on the ASMs heighten rapidly (in the short term) in the event of a sudden increase in geopolitical tensions or risk. This reaction could be due to uncertainty and fear among investors about the potential impact of geopolitical events on economic stability, trade, and business operations. To put differently, geopolitical developments have the potential to trigger market volatility, hence any escalation of geopolitical tensions culminate to heightened investor anxiety, resulting in increased volatility as investors quickly adjust their positions in response to perceived risks.

In Figure 2(b), the plots for EPU and stock market volatilities revealed a strong coherence in the short-term band (0–4 months) in almost all the markets with the exception of NGX and GSE.

The strong correlation between ASM volatilities and economic policy uncertainty index, particularly in the short-term band, underscores the significance of policy-related factors in shaping market dynamics and investor behavior in African markets.

From the findings in Figure 2(b), it can be argued that investors tend to react swiftly to changes in economic policy uncertainty as it introduces ambiguity and unpredictability into the investment ecosystem. This supports a study by Pástor and Veronesi (2013) which established that increased uncertainty has a corresponding increase in risk aversion among investors, leading to higher stock market volatilities as investors are inclined to adjust their portfolios in response to perceived risks. A related study Bloom (2009) contends that uncertainty about future economic policies could result in delayed investment and consumption decisions, leading to higher stock market volatilities as investors revise their expectations about future earnings and economic conditions.

Similarly, a strong short-term interdependency can be observed in Figure 2(c) which displays plots for FS and stock market volatility nexus. From the plots, it can be observed that CSE, EGX, DSE and JSE exhibit extraordinary strong coherence with FSI, particularly in the short term. The short-term correlation observed in Figure 2(c) reflects the increasing interconnectedness of global financial markets. Thus, ASMs are not isolated, and they are influenced by developments in global financial markets, notably interest rate movements, credit spreads, market liquidity, amongst others. Therefore, as can be observed, fluctuations in the FS Index, which captures global financial conditions, can have immediate effects on ASM volatilities.

5. Conclusion

The findings of this study bring to bear that while stock returns in the African market may not be strongly influenced by short-term GPRs, FS, and economic policy uncertainty, stock volatilities do show a significant relationship with these factors. This implies that although market returns might not react immediately to changes in geopolitical events or policy uncertainty, the level of uncertainty and stress in the financial environment do affect the volatility of stock prices.

For the ASM, this carries important implications. Investors and market participants should be aware that while actual returns may not fluctuate dramatically in response to short-term events, the volatility of those returns can still be influenced by factors such as GPRs and economic uncertainty. This suggests that the market might not accurately price in these risks in the short term, potentially leading to periods of heightened volatility without corresponding shifts in actual returns.

In conclusion, it is crucial for investors in the ASM to closely monitor geopolitical developments, FS indicators, and economic policy uncertainty, as these factors can significantly impact stock market volatility, particularly in the short term. Additionally, policymakers should strive for greater transparency and stability in economic policies to help mitigate unnecessary market volatility. Diversification and risk management strategies should also be employed by investors to navigate periods of heightened uncertainty effectively.

5.1 Recommendation for future studies

Researchers should delve deeper into the underlying factors driving the observed patterns in the ASM. Further studies may explore the specific channels through which GPRs, FS and economic policy uncertainty impact stock volatilities, as well as the effectiveness of different risk management strategies for investors operating in the region.

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Corresponding author
David Korsah can be contacted at: Davek347@gmail.com