Economics

Geopolitical risks and stock market volatility in the SAARC region

--Manuscript Draft--

Manuscript Number:	ECONJOURNAL-D-24-00151
Full Title:	Geopolitical risks and stock market volatility in the SAARC region
Article Type:	Research Article
Keywords:	South Asia; stock return; GPR; wavelet; TVP-VAR
Manuscript Region of Origin:	INDIA
Abstract:	This study examines the volatility of the stock markets of the member states of the South Asian Association for Regional Cooperation (SAARC) and geopolitical risk (GPR). The analysis period ranged from January 2014 to March 2024, and data were processed using the time-frequency wavelet method. The time-varying parameter vector autoregression test was used to determine the dynamic connectedness of volatility in the analyzed states. The findings revealed similar stock market connections in Bangladesh and India. In addition, a comparative analysis of stocks in India and Pakistan led to the identification of common elements. The connection between geopolitical concerns and Sri Lankan stocks was the strongest and increased in intensity after 2019. The relationship between GPR and Nepal's stock market was continuous but of low intensity. The dynamic connectedness between member states' stock markets was limited during the review period. The results of this study could encourage SAARC governments to bridge their political differences to ensure that South Asia becomes a strong partner in the global economy. Equally, our results can be useful to investors, financial institutions, regulatory authorities, and governments.
Manuscript Classifications:	3.2: Econometrics; 7.4: General Financial Markets; 14.4: Financial Markets and Institutions

Geopolitical risks and stock market volatility in the SAARC region

Running title: Geopolitical risks and stock market volatility

Oana Panazan, Catalin Gheorghe, Emilia Calefariu

Department of Engineering and Industrial Management, Transilvania University of Brasov, Eroilor Street 29, Brasov 500036, Romania

***Corresponding Author:** Catalin Gheorghe
Email: gheorghe.c@unitbv.ro

Abstract: This study examines the volatility of the stock markets of the member states of the South Asian Association for Regional Cooperation (SAARC) and geopolitical risk (GPR). The analysis period ranged from January 2014 to March 2024, and data were processed using the time-frequency wavelet method. The time-varying parameter vector autoregression test was used to determine the dynamic connectedness of volatility in the analyzed states. The findings revealed similar stock market connections in Bangladesh and India. In addition, a comparative analysis of stocks in India and Pakistan led to the identification of common elements. The connection between geopolitical concerns and Sri Lankan stocks was the strongest and increased in intensity after 2019. The relationship between GPR and Nepal's stock market was continuous but of low intensity. The dynamic connectedness between member states' stock markets was limited during the review period. The results of this study could encourage SAARC governments to bridge their political differences to ensure that South Asia becomes a strong partner in the global economy. Equally, our results can be useful to investors, financial institutions, regulatory authorities, and governments.

Keywords: South Asia, stock return, GPR, wavelet, TVP-VAR.

1. Introduction

In recent years, concern regarding the effects of geopolitical risk (GPR) on stock markets has increased. This trend is justified because GPR is a fundamental element in investment decisions. According to Caldara and Iacoviello (2022), GPR includes events that affect international peace, such as tensions between states or regions, acts of terrorism, military or nuclear threats, political uprisings, elections, and wars. From a methodological perspective, the GPR index is based on the frequency of words denoting geopolitical events appearing in major international newspapers.

The global capital market is a conglomerate comprising large and small entities united by dynamic financial links. The South Asian Association for Regional Cooperation (SAARC) is a component of the world market with certain strengths. It is a local intergovernmental and geopolitical association of South Asian states, including India, Afghanistan, Nepal, Sri Lanka, Bangladesh, Pakistan, Bhutan, and the Maldives. A few statistical coordinates underline the importance of SAARC worldwide. The organization owns 3%, 52.1%, and 21% of the Earth's surface, world economy, and the world's population, respectively, with a nominal gross domestic product (GDP) of USD 4.359 trillion (https://www.worlddata). In addition to the significant population and variety of natural resources, SAARC member states have the potential to develop and grow financial markets (Ellahi et al., 2021). Although member states share a common historical and cultural heritage, political tensions and differences have emerged over time, particularly between India and Pakistan (Sehgal et al., 2018), which could potentially determine a certain volatility of the financial market.

The literature presents the interconnections among developing stock markets of the SAARC and the short- and long-term states of the world economy (Prakash & Kumar, 2014). For example, Srinivasan et al. (2011) employed the Johansen co-integration test to establish a long-run two-way causal connection between GDP and foreign investment in Sri Lanka, Bangladesh, the Maldives, Nepal, India, and Pakistan. The interconnections between SAARC national markets are manifested at both macroeconomic and corporate levels. Thus, in addition to global aspects such as economic growth, long-term debt, and stock market development, significant relationships between profitability, liquidity, and the size of companies in the SAARC region are observed (Shahzad et al., 2021). Singh and Ahmed (2016) revealed the degree of financial and currency co-integration of less-developed states in the Asia-Pacific region using a multivariate dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model. They demonstrated that SAARC states are inter-regionally integrated with the Association of South East Asian Nations (ASEAN) and the Pacific area. Surprisingly, very little research has been conducted on stock volatility and returns in the SAARC states. Moreover, certain controversies have been identified in the literature regarding the interconnections between SAARC states, which are not unanimously accepted by researchers. For example, Sehgal et al. (2017), employing temporal fluctuations Copula GARCH models, document that the connection with the foreign exchange market is small in the South Asian region (Sehgal et al., 2017); the analysis period was between January 6, 2004, and March 31, 2016. In addition, the SAARC area seems prone to the formation of speculative bubbles, characterized by the sudden increase in the prices of financial assets, followed by their sudden decrease (Liaqat et al., 2020; Nazir et al., 2020; Tran, 2017).

Wavelet analysis enhances the relationship between stock returns and GPR simultaneously in terms of timing and frequency areas. Wavelet transforms generate a one-dimensional time series that allows for the achievement of research objectives. Because of its advantages over classical statistical methods, wavelet analysis is frequently used in the study of financial time series (Bouri et al., 2020; Chien et al., 2021; W. Li et al., 2022; Li et al., 2024). This study used two analysis tools based on a continuous wavelet transform: wavelet coherence and wavelet phase difference.

Taking the gaps indicated in the literature as a starting point, the goals of the research were as follows: (i) evaluate the dynamic movements involving the SAARC member states' stock markets by applying wavelet analysis, (ii) estimate the intensity of the relationship between GPR events and the volatility of stocks in the analyzed states, and (iii) use the time-varying parameter vector autoregression (TVP-VAR) method for establishing dynamic volatility connectedness between markets in the analysis period.

The paper proceeds as follows. Section 2 presents a synthesis of the literature on GPR and stock volatility in the SAARC states. Section 3 presents the data, series, and techniques applied. Sections 4 and 5 present the outcomes and connections, respectively, of similar studies. Section 6 presents the conclusions, limitations, and possible future research directions.

2. A Literature review

Volatility of a stock refers to the risk of price change caused by continuous adjustments to new information. Early literature demonstrates how periods of high uncertainty affect financial markets, the behavior of market agents, and, implicitly, the evolution of economies (Antonakakis et al., 2014; Brogaard and Detzel, 2015). During episodes of high volatility, the tradeoffs between volatility and financial stress appear to increase in different geographic regions (Johansson, 2008). Moreover, periods characterized by high levels of uncertainty reduce returns (Arouri et al., 2016).

We believe that the GPR index can be used in SAARC states to cover major geopolitical events, such as the Tripura rebellion (1989–present), the communist war in Afghanistan (1989–1992), ethnic conflict in Nagaland (1993–present), Afghanistan War (2001–2021), war in North-West Pakistan (2004–present), the Islamic State–Taliban conflict (2015–present), India–Pakistan military confrontation (2016), republican insurgency in Afghanistan (2021–present), Afghanistan–Iran clashes (2021 and 2024), the 9/11 attacks in the US, the Gulf War (1990–1991), annexation of the Crimean Peninsula (2014), terror attacks in Paris (2015), growing Syrian conflict (2011–present), US–North Korea tensions over nuclear proliferation (2012–present), the proxy war between Qatar and Saudi Arabia (2011–present), US–China tensions (2018–2020), the COVID-19 outbreak (2019), and the invasion of Ukraine (2022). The listed GPRs influenced stock markets in the SAARC region, increasing volatility and reducing financial market stability.

Most studies of stock returns or volatility focus on a single SAARC member state. Following the research portals, we found that most research focuses on India (P. Chaudhary, 2021; Sreenu, 2023; Upadhyaya et al., 2023), followed by Pakistan (Rashid et al., 2022; Umar et al., 2023), Bangladesh (Sahabuddin et al., 2021; Uddin et al., 2020), Sri Lanka (Maiti, 2019), and Nepal (Saud & Shakya, 2020). Although we found studies on stock returns that include one or more SAARC member states, they do not consider the organization as a whole (Habiba et al., 2020; Jebran & Iqbal, 2016; Morawakage et al., 2019; Shafiq et al., 2023).

Global or regional geopolitical events affect neighboring markets because of the contagion effect. Research, which intensified after the war in Ukraine, reveals that GPR events affect stocks (Raheem, & Le Roux, 2023), commodities (Gong & Xu, 2022), gold (Adeosun et al., 2024), oil (Ahmed et al., 2023; He & Sun, 2024), energy (Böyükaslan et al., 2024; Mamman et al., 2024; Wang et al., 2024), and cryptocurrencies (Aysan et al., 2019; Singh et al., 2022). The emergence of GPR has caused investors to migrate to heavy assets (Elsayed et al., 2022) for protection against risk. In general, research in the SAARC region has examined the contagion effect from developed markets. For example, Aziz et al. (2021) examined the spread of volatility from the United States to the stock markets of SAARC member countries, including Pakistan, India, Bangladesh, and Sri Lanka, using an exponential GARCH (EGARCH) model. According to the authors, the spillover effect varied over time and was negative in most SAARC states. Bangladesh's stock market was the most impacted, whereas Pakistan's stock market volatility did not depend on the forecast horizon.

Studies addressing the influence of GPR events on SAARC states have shown contradictory results. N. Chaudhry et al. (2018) studied the effects of terrorism on stocks in India, Bangladesh, Sri Lanka, and Pakistan. They argue that Sri Lanka and Bangladesh were less affected than Pakistan and India. Arya and Singh (2022) examined four SAARC states (India, Sri Lanka, Pakistan, and Bangladesh) between February 2013 and March 2021, demonstrating that the COVID-19 pandemic negatively influenced stock returns in the analyzed countries. According to Gajurel and Chawla (2022), SAARC states are the least studied and unexplored of Asian markets.

Yang et al. (2021) report a similar perspective, highlighting the paucity of studies on equity volatility in emerging markets.

Although the previous paragraphs summarize the research progress on the interconnection between GPR events and volatility in the SAARC states, literature on this topic is scarce. To the best of our knowledge, no previous research has examined the relationship between GPR events and the volatility of SAARC stock markets over the period under review. Thus, this study aims to bridge this gap in the literature.

3. Data and methodology

To determine volatility, the daily closing prices of the benchmark for each analyzed state were collected. Daily rates were taken from Investing (https://www.investing.com), an electronic platform, for the period from January 1, 2014, to March 5, 2024. For the GPR index, daily data was collected using the platform (https://www.matteoiacoviello.com/gpr.htm). The start date was based on the 45th Session of the SAARC Programming Committee. The closing date corresponds to its 59th session at Kathmandu (https://www.saarc-sec.org), a landmark event in the process of regional cooperation in South Asia. We identified data for five of the eight South Asian countries that constitute SAARC. No observations were available for Bhutan and Afghanistan, and in the case of the Maldives, the Maldives Stock Exchange Index (MASIX) does not include daily observations, which may lead to erroneous results. The benchmarks selected for this study are listed in Table 1. The authors respected ethical practices throughout the research phase. Thus, the research is conducted in such a way as to generate accurate and reliable results. Research involves going through several stages. In the first stage, equal time series are compiled for each state's stock exchange volatility and the GPR index. Subsequently, a pair of series is formed between the volatility of the indices and the GPR index. In the second step, stationarity and multicollinearity tests are run. In the third step, the wavelet transform is applied between the pair of series. In the fourth stage, the phase differences between the pairs of series are realized, to establish the leading variable and the type of correlation between the variables at different frequencies. The verification of the results is carried out in the last stage using to determine the dynamic connectedness of volatility in the analyzed states.

Table 1. The selected indices

State	**Index**
Bangladesh	DSE30
India	SENSEX30
Pakistan	KSE
Sri Lanka	CSE
Nepal	NEPSE

To determine volatility, the natural logarithm of the daily closure values was considered. Daily returns are calculated as the initial difference of the converted series.

$$R_{i,t} = \ln(Index_t) - \ln(Index_{t-1}) \quad (1)$$

where $R_{i,t}$ is the index return volatility, and $Index_t$ and $Index_{t-1}$ are the closing stock market index prices on consecutive days.

Similar to the normal Augmented Dickey-Fuller (ADF) unit root, Phillips Peron (PP), and Kwiatkowski-Phillips-Schmidt-Shin test statistics (KPSS) testing against stationarity, tests for exuberance are typically conducted with transient dynamics added to the model specification. Subsequently, the empirical regression model can be expressed as follows (Phillips et al., 2015).

$$y_{i,t}= \delta_i + \beta_i t + \varphi_t + \gamma_{1t}x_{1it} +\ldots+\gamma_{Mi}x_{Mit} + \epsilon_{it} \tag{2}$$

where the number of time observations and cross-sectional units are represented as i = 1,...,N, t = 1,...,T, and M is the number of regressors. δ_i, $\beta_i t$, and φ_t represent a unique, individual effect, one particular linear trend, and typical time effect, respectively. The coefficients' heterogeneity is represented by γ_{Mi}. The objective of the ADF and PP tests is to examine the unit-root null hypothesis H_0:β=1 in contrast to explosiveness, the right-tailed alternative H_1: β >1. The objective of the KPSS test is to investigate the stationarity of the series.

A finite interval function can be used to create a wavelet Ψ(x), which is the fundamental wavelet. A group of fundamental wavelets $\{\Psi_{m,n}(x)\}$ can be acquired by expanding and translating fundamental wavelet Ψ(x) as follows:

$$\Psi_x(m,n)= \left|\frac{1}{\sqrt{m}}\right| \Psi\left(\frac{x-n}{m}\right) \tag{3}$$

where m is a scale factor considering the expansion of Ψ(x), and n is the parameter capturing the location of the translation.

A simple wavelet function Ψ(x) is projected using the continuous wavelet transform (CWT), specified as follows.

$$\Phi_x(m,n)= \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{m}}\Psi\frac{t-n}{m}dt \tag{4}$$

Several wavelet coefficients Z, which depend on the scaling and location parameters, are the outcomes of the CWT. In the time-frequency domain, the CWT is used to ascertain how the two variables interact (Torrence & Compo, 1998).

$$Y^2(m,n)= \frac{\left|S\left(s^{-1}\Phi_{xy}(m,n)\right)\right|^2}{S(s^{-1}|\Phi_x(m,n)|^2)S\left(s^{-1}\left|\Phi_y(m,n)\right|^2\right)} \tag{5}$$

where S denotes a smoothing parameter. The value of Y^2(m,n) ranges from 0 to 1. Stronger reliance between vectors at a given temporal frequency is indicated by greater values.

To highlight positive or negative correlations, the wavelet phase difference proposed by Bloomfield et al. (2004) was established using the following relationship:

$$\varphi_{xy}(m,n)=\tan^{-1}\left(\frac{\mathrm{Im}\left\{S\left(s^{-1}W_{xy}(m,n)\right)\right\}}{\mathrm{Re}\left\{S\left(s^{-1}W_{xy}(m,n)\right)\right\}}\right) \tag{6}$$

where Im represents the imaginary parts, and Re represents the real parts.

Wavelet analysis can reflect the subtle changes and characteristics of the connection between GPR and stock volatility in the time-frequency field, allowing us to simultaneously analyze the strength of the link and the varying characteristics of stock returns at different frequencies.

The expression $\varphi_{xy}(m,n)\in(-\pi,+\pi)$ is the real function, and Im represents the imaginary part of the wavelet transform function. Co-movement between x and y is based on the phase difference

φ_{xy} similar to Agyei (2023). When $\varphi_{xy} \in \left(0, \frac{\pi}{2}\right)$, it implies that x and y have a positive connection, and x leads y. If $\varphi_{xy} \in \left(0, -\frac{\pi}{2}\right)$, y leads x. By contrast, if $\varphi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, it implies that x and y have a negative relationship, and x leads y. Finally, if $\varphi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right)$, y leads x.

We use the TVP-VAR test proposed by Antonakakis and Gabauer (2017) derived from the model developed by Diebold and Yilmaz (2014), which allows the variations to evolve via a stochastic Kalmen Filter estimation (Koop & Korobilis, 2014). The improved version insensitive to outliers model, avoiding the loss of observations, is applied (Antonakakis et al., 2020). The choice of the model is based on the advantages generated, compared with classical models such as the Granger causality test, correlation coefficient, Copula, and rolling-window VAR model (Kaur & Mittal, 2023; T. Liu & Shigeyuki, 2021; Zhao et al., 2022). The model has been preferred in the study of stock volatility in recent years (He & Sun, 2024; Jana & Sahu, 2023; W. Li et al., 2022). The model involves the application of several relationships presented below:

$$X_t = B_t z_{t-1} + u_t; \qquad u_t | \Omega_{t-1} \sim N(0, \Sigma_t) \tag{7}$$

$$\mathrm{vec}(B_t) = \mathrm{vec}(B_{t-1}) + v_t; v_t | \Omega_{t-1} \sim N\left(0, \xi_t\right) \tag{8}$$

and

$$z_{t-1} = \begin{pmatrix} X_{t-1} \\ X_{t-2} \\ \vdots \\ X_{t-p} \end{pmatrix}, B_t^{'} = \begin{pmatrix} B_{1t} \\ B_{2t} \\ \vdots \\ B_{pt} \end{pmatrix} \tag{9}$$

where X_t are N×1 vectors, z_{t-1} are N_p×1 vectors, u_t is an m×1 vector, v_t is an m_p^2×1 dimensional vector, B_t are m×mp dimensional matrices, B_{it} are m×m dimensional matrices, and Σ_t and ξ_t are variance–covariance having m×m and m_p^2× m_p^2 dimensions. The vectorization of B_t is represented by the $\mathrm{vec}(B_t)$ vector, having m_p^2×1 dimensions.

The dynamic connectedness index uses generalized forecast error variation decompositions (GFEVD) (Koop & Korobilis, 2014; Pesaran & Shin, 1998). The step error variance h in forecast variable i is due to shocks to variable j.

$$\tilde{\phi}_{ij,t}^{g}(h) = \frac{\sum_{t=1}^{h-1} \psi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{h-1} \psi_{ij,t}^{2,g}}, \tag{10}$$

$$\sum_{j=1}^{N} \tilde{\phi}_{ij,t}^{g}(h) = 1 \text{, and } \sum_{ij=1}^{N} \tilde{\phi}_{ij,t}^{N}(h) = N, \tag{11}$$

where h-step ahead GFEVD is represented by $\tilde{\phi}_{ij,t}^{g}(h)$.

The spillover transmitted by the variable i to all variables j, or the total directional connection TO others, is determined by the relation

$$TO_{jt} = C_{i\to j,t}^{g}(h) = \frac{\sum_{j=1,\, i\neq j}^{N} \tilde{\phi}_{ij,t}^{g}(h)}{\sum_{j=1}^{N} \tilde{\phi}_{ij,t}^{g}(h)} \cdot 100. \tag{12}$$

The spillover received by variable i from other variables j, or the total directional connection FROM others, is as follows.

$$\mathrm{FROM}_{jt} = C^{g}_{i\leftarrow j,t}(h) = \frac{\sum_{j=1,\, i\neq j}^{N} \tilde{\phi}^{g}_{ij,t}(h)}{\sum_{j=1}^{N} \tilde{\phi}^{g}_{ij,t}(h)} \cdot 100. \tag{13}$$

The difference between variables TO and FROM has the significance of the total NET directional connection:

$$\mathrm{NET}_{jt} = \mathrm{TO}_{jt} - \mathrm{FROM}_{jt} = C^{g}_{i\rightarrow j,t}(h) - C^{g}_{i\leftarrow j,t}(h)_{jt}. \tag{14}$$

$\mathrm{NET}_{jt}>0$ indicates a net transmitter, while $\mathrm{NET}_{jt}<0$ has the significance of a net receiver. Global connectedness, GC, is determined as follows:

$$\mathrm{GC}_{ij} = \frac{\sum_{j=1}^{N} \mathrm{TO}_{jt}}{N} = \frac{\sum_{j=1}^{N} \mathrm{FROM}_{jt}}{N} \tag{15}$$

4. Results

Table 2 presents the descriptive statistics of the analyzed stock indices. All analyzed series exhibit excess kurtosis. High amplitude values were recorded in the DSE30 index (726.426), followed by SENSEX30 (30.642) and CSE (20.047), while the lowest amplitude was identified in the NEPSE index (8.109). The Jarque-Bera test determines the skewness and kurtosis of a dataset, indicating the shape of the distribution. In the case of the analyzed series, the null hypothesis of the test was rejected, confirming that the series significantly differs from a normal distribution.

Table 2. Descriptive statistics

Indicator	**DSE30**	**SENSEX30**	**NEPSE**	**KSE**	**CSE**
Mean	0.00024	0.00040	0.00030	0.00028	0.00017
Maximum	0.53462	0.08594	0.05884	0.06048	0.06927
Minimum	-0.51697	-0.14101	-0.06226	-0.07102	-0.08444
Standard Deviation	0.01781	0.00936	0.01133	0.00953	0.00885
Skewness	9.00672	-1.49091	0.45748	-0.55626	-0.82645
Kurtosis	726.4266	30.6425	8.10954	9.28152	20.04705
Jarque-Bera	68339	10087.6	3516.269	5310.733	38280.11
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	0.76682	1.27859	0.95069	0.89762	0.54775
Sum Squared Deviation	0.99345	0.27459	0.40249	0.28484	0.24544
Observations	3132	3132	3132	3132	3132

To apply the wavelet method, the stationarity condition of the analyzed time sequence should be satisfied. ADF, PP, and KPSS tests were applied to confirm the nature of time sequence data (Table 3). The selected tests allow the assessment of the unit root for each time series. The null hypothesis of the PP and ADF trials indicates the existence of the unit root in the series, while that of the KPSS test indicates the stationarity of the series. All constructed series exceeded the stationarity condition.

Table 3. Stationarity tests

Index	ADF		PP		KPSS	
	t-Statistic	**Prob.***	**Adj. t-Stat**	**Prob.***	**LM-Stat.**	**Prob.***
DSE30	-65.48329	0.0001	-79.17769	0.0001	0.2324	0.4418
1%	-3.43224		-3.43224		0.739	
5%	-2.86226		-2.86226		0.463	
10%	-2.5672		-2.5672		0.347	
SENSEX30	-56.87565	0.0001	-56.87125	0.0001	0.0416	0.0148
1%	-3.43224		-3.43224		0.739	
5%	-2.86226		-2.86226		0.463	
10%	-2.5672		-2.5672		0.347	
NEPSE	-36.17777	0.0000	-54.37915	0.0001	0.1446	0.1342
1%	-3.43225		-3.43224		0.739	
5%	-2.86226		-2.86226		0.463	
10%	-2.5672		-2.5672		0.347	
KSE	-35.47011	0.0000	-52.38057	0.0001	0.1023	0.0927
1%	-3.43225		-3.43224		0.739	
5%	-2.862265		-2.86226		0.463	
10%	-2.5672		-2.5672		0.347	
CSE	-48.09222	0.0001	-49.93313	0.0001	0.1219	0.2691
1%	-3.43224		-3.432249		0.739	
5%	-2.86226		-2.8622		0.463	
10%	-2.5672		-2.5672		0.347	

Next, time series of lengths equal to the number of observations in Table 2 were made. Pairs containing the GPR index and the return of every stock index were formed. In this way, five pairs of series were obtained for which wavelet coherence and wavelet coherence phase difference were applied. The outcomes are presented as scalograms in Figure 1. Such graphs are frequently used in the study of the yield and volatility of financial assets (Aysan et al., 2023; Jiang & Yoon, 2020; Mensi et al., 2021; Nasir & He, 2023; Ziadat et al., 2024).

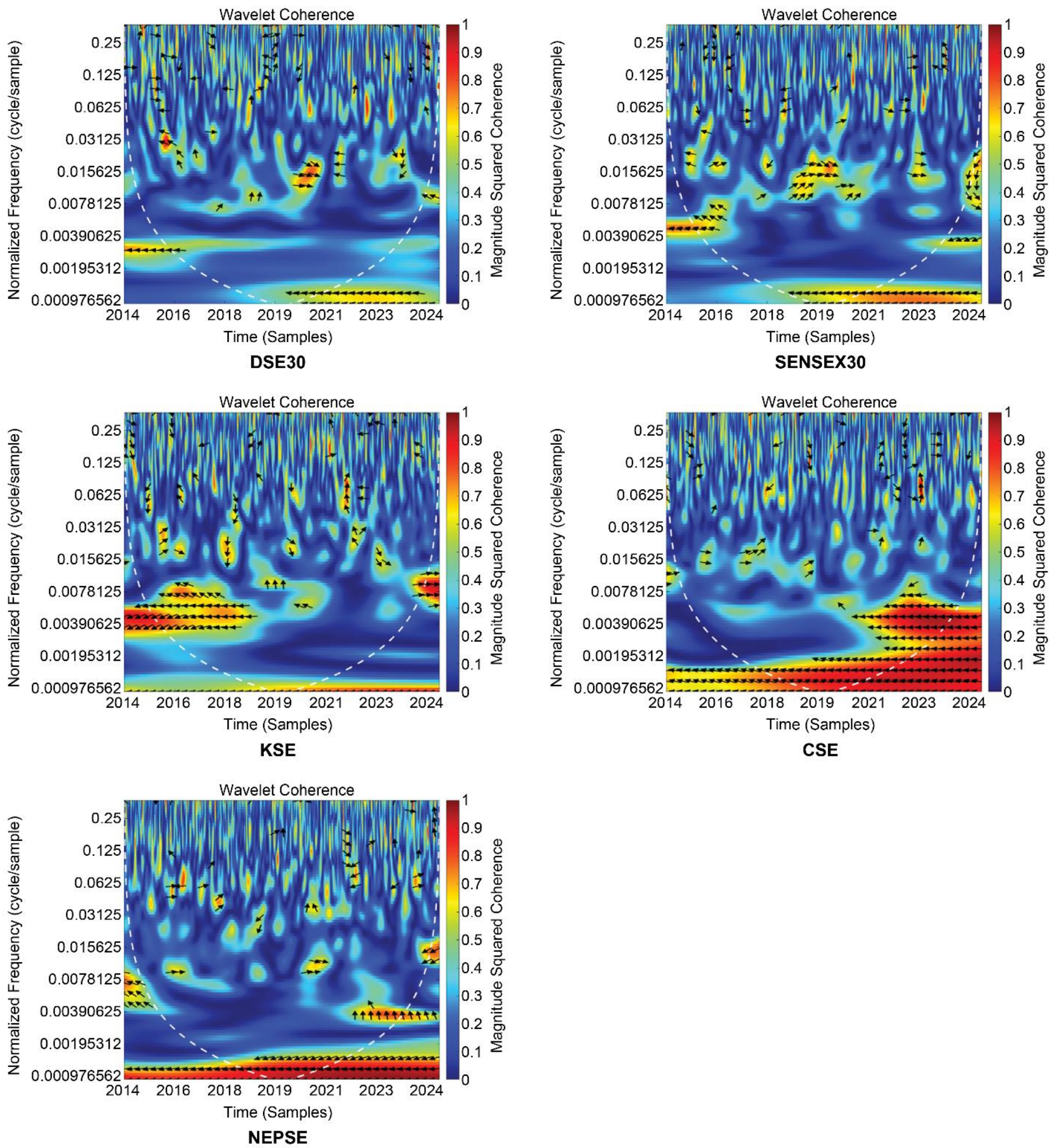


Figure 1. Continuous wavelet transform of GPR and SAARC stock returns

The Ox axis represents the time (days) and the Oy axis represents the normalized frequency (coefficient between 0 and 1). Each graph contains a color gradient between dark blue (minimum value) and dark red (maximum value). The blue regions indicate a weak relationship between the variables; the red regions indicate a strong relationship between GPR and yield. Eight unidirectional arrows appear in each scalogram. The arrowhead (→) indicates that the time sequence is in phase (positively correlated), while (←) indicates that the sequence is outside of phase (negatively correlated). The arrowheads (↗) and (↙) show that the initial variable (GPR) has the leading function. The arrowheads (↘) and (↖) indicate the leading function for the second variable (stock returns). The arrowheads (↑) and (↓) indicate that there is a phase shift of $\pi/2$ between the analyzed series.

5. Discussion

Figure 1 shows a heterogeneous relationship between GPR and stocks in the SAARC states. A common feature of the states that was examined is the short-term appearance in the high normalized frequency band (0.0625–0.2) of a large number of adjacent thin vertical regions. Such fluctuations are normal in the stock market and denote the self-adjustment of the market to GPR events of less importance (Chen, 2023; Yu et al., 2015). The red regions present in the scalograms for Pakistan, Sri Lanka, and Nepal indicate that the engagement between GPR and stock returns varies on the investment horizon (Agyei, 2023).

5.1 GPR and Bangladeshi stocks

Figure 1 shows how GPR and stock returns are traded off in Bangladesh. The heatmap is mostly blue, illustrating poor coherence during the sampling period. Average coherence is observed in the lower-left quadrant during 2014–2016, suggesting the impact of GPRs (the political rivalry between the Awami League and Bangladesh National Party) on the financial market. The series are negatively correlated, and the leading role belongs to the GPR. Weak coherence is observed in the lower-right quadrant throughout the COVID-19 pandemic. News about the spread of the virus affected stock returns from the beginning of the pandemic until early 2021. There are a few consistent features of the lead–lag connections between GPR and stock markets and an almost permanent long-term lead–lag connection in all pairs, as seen from the arrows to the left. This indicates a negative connection between the vectors and that the yield plays the main role. In the intermediate term, the arrowheads continuously point to the right, suggesting a favorable association. In the short term, a permanent relationship between variables cannot be identified, and the arrows are oriented differently (Dahir et al., 2018). One interesting aspect is the similar evolution of stock markets in Bangladesh and India. The muted effect of stock volatility in Bangladesh may have been influenced by the trade between the two states. China and India, being the largest importers, are known to affect Bangladeshi stock market performance (Gajurel & Chawla, 2022; Uddin et al., 2020). These results reveal that Bangladeshi stocks acted as long-term diversifiers during the analyzed period, especially between 2014 and 2020.

5.2 GPR and Indian stocks

For India, the heat map is mostly blue, except for some yellow-orange arrow islands in the low- and medium-normalized frequency bands. Average coherence was recorded during 2014–2016, marked by a negative correlation between GPR and Indian stocks. A similar situation emerged between the second half of 2018 and 2021, which may have been caused by the ongoing Tripura rebellion or ethnic conflict in Nagaland. After the onset of the pandemic in 2020 until the end of the sample period, a negative relationship is observed between GPR and stocks in India. This link can be attributed to the war in Ukraine, which began in February 2022. Using an approximate conditional correlation DCC-GARCH multivariate model, Singh and Ahmed (2016) suggested that a change in the dynamics was observed in the correlation of South Asian least-developed countries' exchange rates with China after the global financial crisis. Contrary to Agyei's study (2023), our results demonstrate that at the start of the conflict in Ukraine, GPRs led Indian stocks, but the relationship was positive only at the beginning of the pandemic in the medium-frequency band and negative otherwise. Compared with Bangladeshi stocks, Indian stocks offer medium-term hedging potential. These dynamics allow risk-averse investors to diversify their portfolios.

5.3. GPR and Pakistani stocks

Pakistan is a unique case, although the heat chart is mostly blue. The bottom-left quadrant of the chart contains a consistent red region in the average-normalized frequency band. In the period 2014–2018, a negative correlation between GPR and stocks is observed due to the India–Pakistan military confrontation. In the same frequency band, a small red positively correlated region is noted from the end of 2023 until the end of the sampling timeframe. We believe that this represents the effect of the war in Ukraine, which has had a smaller impact on the Pakistani stock market than on the Indian stock market.

A comparative analysis of the scalograms of India and Pakistan leads to the identification of commonalities. The size of the scalograms and the orientation of the arrows reveal that the volatility of both stock markets is similarly impacted by the arrival of GPR news. We extend the evidence presented by Ahmed and Hussain (2014) to the documented period. Moreover, we agree that Indian stock market volatility is more moderate to the occurrence of GPRs, whereas its effect on Pakistan's capital markets is more pronounced. Khan et al. (2022) demonstrate that terrorism has a substantial effect on Pakistani stock returns and volatility; they use GARCH models over the sample period ranging from October 7, 1999 to May 31, 2016. We believe that the authors' conclusions are correct and can be extended to 2023. Aslam et al. (2021) evaluate the effect of terrorism on stock market volatility in Pakistan. Their results summarize the impact of 339 acts of terrorism over 18 years (2000–2018). Our results confirm their conclusions that the GPR index is more comprehensive. Such results can be used as hedging or safe-haven possibilities according to the indicated time frequencies. In summary, Pakistani stocks offer opportunities for long-term diversification throughout the sample period, especially between 2014 and 2019, and for medium-term hedging.

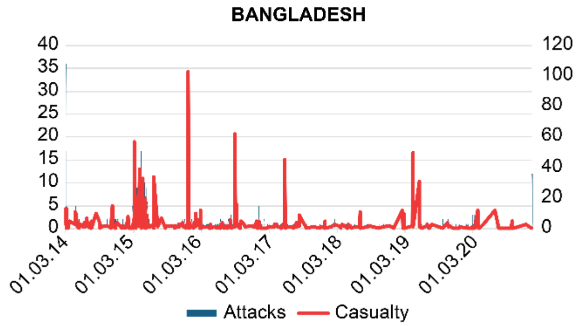
5.4 GPR and Sri Lankan stocks

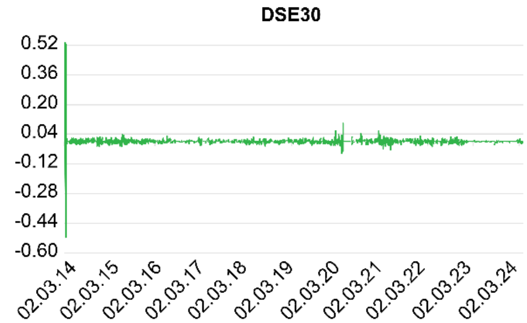
Sri Lanka's heat map is marked in red. The link between GPR and Sri Lankan stocks is the strongest. Throughout the analysis period, a negative relationship between GPR and stocks is found, increasing in intensity from 2019 until the end of the analysis period. We believe this is because Sri Lanka is still facing an economic crisis that strongly impacts the stock market (https://www.hrw.org). Our results complement those of Z. Li et al. (2023), who highlight the oil supply risk of Southeast Asian nations and demonstrate that Sri Lanka and Nepal are particularly vulnerable to oil supply disruptions, and that the Maldives, Nepal, and Sri Lanka are at low risk. Their results can be extended to the risk of GPRs in Nepal and Sri Lanka. Investors become more careful with their investments, especially during GPR events, and, consequently, seek safer assets.

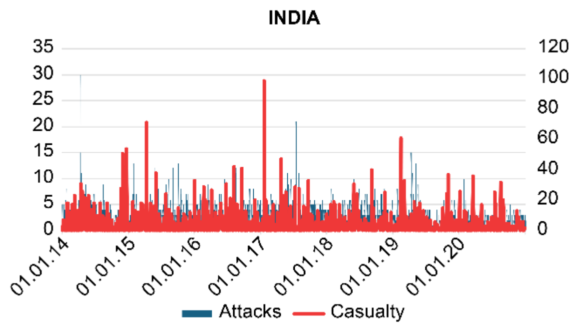
5.5 GPR and Nepali stocks

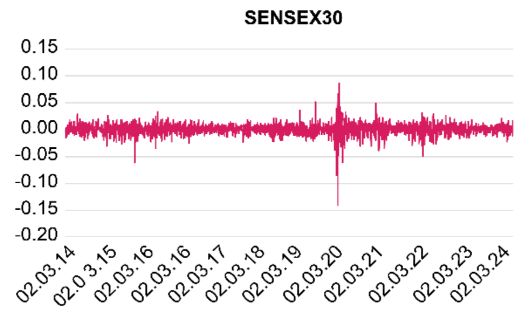
Another state affected by GPR during the analysis period is Nepal. Although the relationship between the variables is negative, the intensity with which stocks in Nepal react to GPR is much lower but continuous, as indicated by the yellow-red band near the Ox axis. As of 2019, GPR was leading the stocks in Nepal. India and Nepal share a common border with China. Considering these aspects, the episodes of volatility found in the scalograms related to these states may be influenced by China's financial market. GPRs are known to negatively affect trade (Yang et al., 2021). Therefore, consistent with Adhikary (2017), we support the idea that international trade accentuates the effect of GPR on financial markets. Both negative and positive effects of China's financial market may be amplified in SAARC states. The effect of GPR is greater in economies with higher investment levels (Khraiche et al., 2023). The stock dynamics in Nepal provide an opportunity for fixed-income investors to hedge GPR risks over the medium term. Additionally, the possibility of long-term hedging is noted throughout the sampling period.

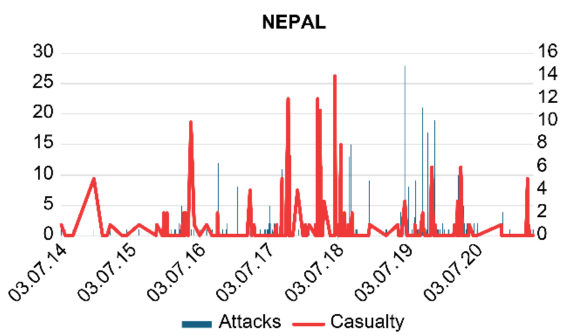
Limited space prevents us from commenting on all the GPR events in the literature synthesis. We consider it appropriate to extract two frequently encountered events in the SAARC area: terrorist attacks and casualties (Aslam et al., 2021; N. Chaudhry et al., 2018). Graphs were constructed using the data downloaded from The Global Terrorism Database™ (GTD) (https://www.start.umd.edu/gtd). GTD observations include details on the incidents' date and location, weapons utilized, and the number of casualties. Figure 2 depicts the relationship between the two retained variables and their effects on volatility.

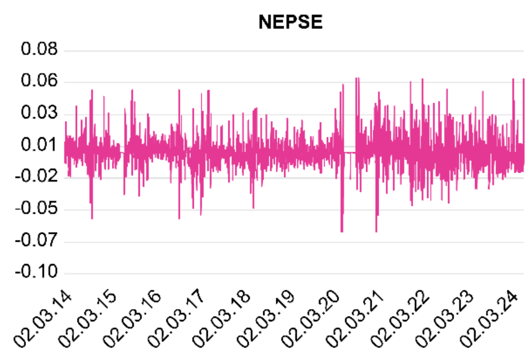

BANGLADESH
40 35 30 25 20 15 10 5 0
120 100 80 60 40 20 0
01.03.14 01.03.15 01.03.16 01.03.17 01.03.18 01.03.19 01.03.20
Attacks
Casualty

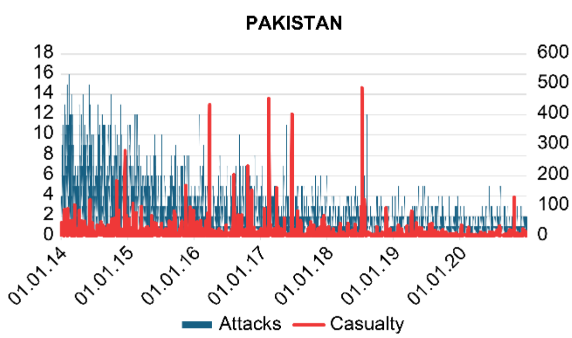

DSE30
0.52 0.36 0.20 0.04 -0.12 -0.28 -0.44 -0.60
02.03.14 02.03.15 02.03.16 02.03.17 02.03.18 02.03.19 02.03.20 02.03.21 02.03.22 02.03.23 02.03.24

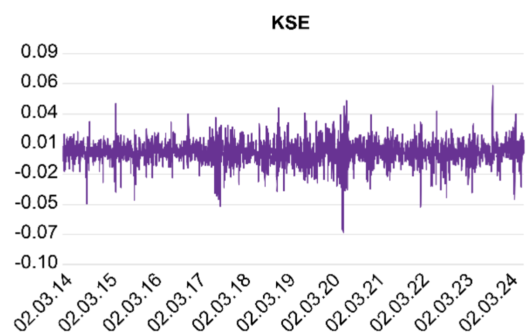

INDIA
35 30 25 20 15 10 5 0
120 100 80 60 40 20 0
01.01.14 01.01.15 01.01.16 01.01.17 01.01.18 01.01.19 01.01.20
Attacks
Casualty

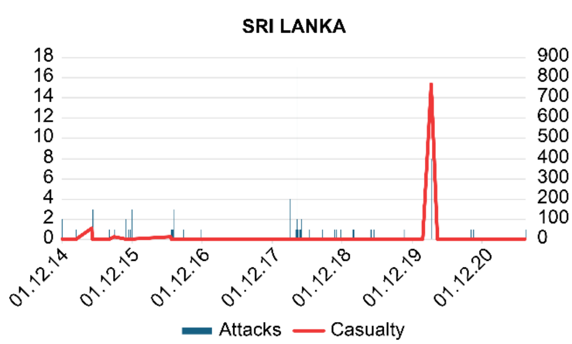

SENSEX30
0.15 0.10 0.05 0.00 -0.05 -0.10 -0.15 -0.20
02.03.14 02.0 3.15 02.03.16 02.03.16 02.03.17 02.03.18 02.03.19 02.03.20 02.03.21 02.03.22 02.03.23 02.03.24


NEPAL
30 25 20 15 10 5 0
16 14 12 10 8 6 4 2 0
03.07.14 03.07.15 03.07.16 03.07.17 03.07.18 03.07.19 03.07.20
Attacks
Casualty


NEPSE
0.08 0.06 0.03 0.01 -0.02 -0.05 -0.07 -0.10
02.03.14 02.03.15 02.03.16 02.03.17 02.03.18 02.03.19 02.03.20 02.03.21 02.03.22 02.03.23 02.03.24


PAKISTAN
18 16 14 12 10 8 6 4 2 0
600 500 400 300 200 100 0
01.01.14 01.01.15 01.01.16 01.01.17 01.01.18 01.01.19 01.01.20
Attacks
Casualty


KSE
0.09 0.06 0.04 0.01 -0.02 -0.05 -0.07 -0.10
02.03.14 02.03.15 02.03.16 02.03.17 02.03.18 02.03.19 02.03.20 02.03.21 02.03.22 02.03.23 02.03.24


SRI LANKA
18 16 14 12 10 8 6 4 2 0
900 800 700 600 500 400 300 200 100 0
01.12.14 01.12.15 01.12.16 01.12.17 01.12.18 01.12.19 01.12.20
Attacks
Casualty

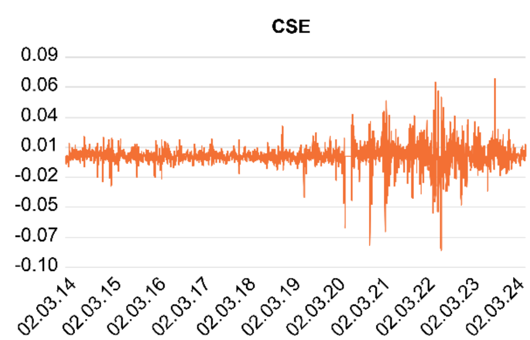

CSE
0.09 0.06 0.04 0.01 -0.02 -0.05 -0.07 -0.10
02.03.14 02.03.15 02.03.16 02.03.17 02.03.18 02.03.19 02.03.20 02.03.21 02.03.22 02.03.23 02.03.24

Figure 2. Daily attacks and casualties (left column) and index volatility (right column)

5.6 Robustness test

Table 4 provides the average dynamic connectivity values for selected index volatilities in our sample and GPR using the TVP-VAR-based connectivity approach.

Table 4. Averaged dynamic connectedness

	Bangladesh	India	Nepal	Pakistan	Sri Lanka	GPR	FROM
Bangladesh	96.3	0.67	0.77	0.92	0.67	0.68	3.70
India	1.09	94.69	0.65	2.48	0.78	0.31	5.31
Nepal	0.76	0.31	97.18	0.41	0.43	0.91	2.82
Pakistan	1.39	2.44	0.69	93.53	1.54	0.41	6.47
Sri Lanka	1.05	0.78	0.66	1.55	95.30	0.66	4.70
GPR	1.07	0.25	0.85	0.31	0.50	97.02	2.98
TO	5.36	4.45	3.62	5.67	3.92	2.97	25.99
NET	1.66	-0.86	0.79	-0.80	-0.78	-0.01	4.33

Note: FROM is the average total directional connectedness received from other countries; TO is the average total directional connectedness contributed to other countries; and NET is the average total net connectedness.

a

The results indicate that the connectivity among SAARC markets, as represented by the total connectivity index, is 4.33%. Consequently, a small percentage (approximately 4%) of the variation in one of the SAARC markets is outlined by the connection between the GPR and the markets analyzed. This confirms the final conclusion drawn by Sehgal et al. (2017) regarding low connectivity between South Asian states. The NET row in Table 4 shows that Bangladesh (+1.66%) and Nepal (+0.79%) are spillover transmitters, while India (− 0.86%), Pakistan (− 0.8%), and Sri Lanka (− 0.78%) are net recipients. That three out of five markets are net gainers reveals that they provide a possible hedge in providing some opposition to the shocks induced by GPR.

Figure 3 shows the evolution of the dynamic connection of total volatility. We see that the interconnectedness of risks fluctuates over time, taking into account major events that have had a substantial impact on the SAARC region. Our findings demonstrate variable features over the sampling period, significant only during GPR events. Outside of them, the level of connectivity is reduced. Under these conditions, it is important to understand the dynamics of connections between SAARC markets during periods of economic turbulence. The implication of these results is that GPR events can reduce the benefits of diversification among SAARC-area stocks. Without proper hedging strategies, investors are exposed to high risk and vulnerability.

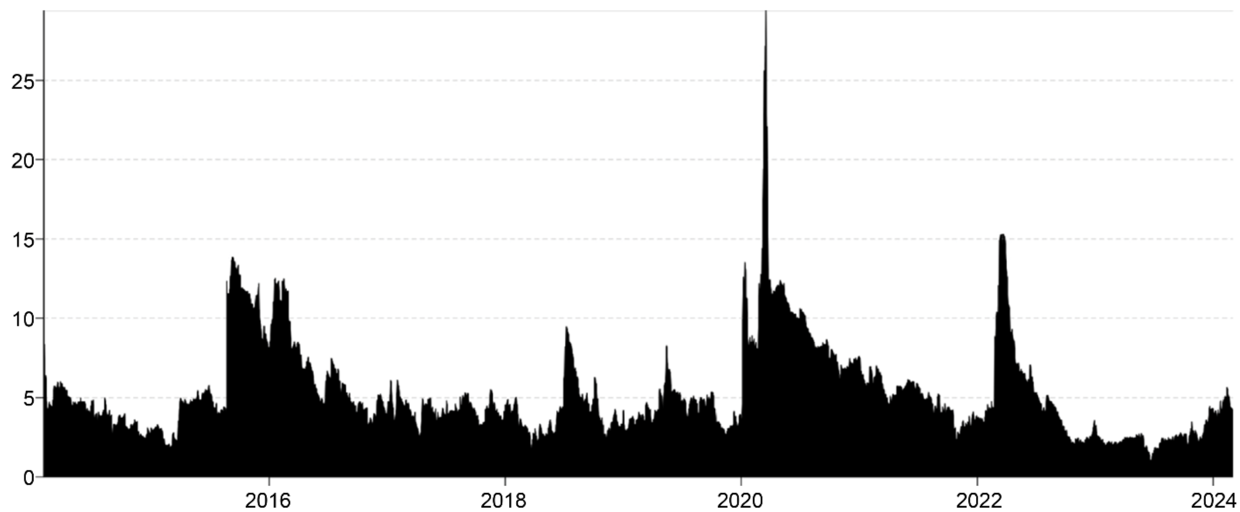


Figure 3. Dynamic total connectedness

Through this research, we contribute to the literature in several ways. We provide information related to the impact of GPR on an area scarcely studied in the literature. We present evidence of GPR events heterogeneously influencing stock markets across SAARC states during the review period. We find that the stock markets in Sri Lanka and Nepal react to GPR stimuli throughout the analysis period. The TVP-VAR robustness test was conducted to determine the spread of volatility across SAARC states. The results indicate that GPR events influence stock returns and volatility. We also reveal the level of interconnections between the analyzed states. All of this evidence may be useful for SAARC management, national market regulators, portfolio managers, and investors.

6. Conclusions and implications

This study examines the impact of GPR events on stocks in SAARC states between January 1, 2014 and March 5, 2024 using the wavelet method. We extracted two frequently encountered events in the SAARC area—terrorist attacks and casualties—and presented their effect on stock volatility, and employed the TVP-VAR connectedness test to analyze the dynamic connection across GPR events and SAARC stock market volatility. The results can be summarized as follows. First, we find that the GPR events we studied affected the stock markets heterogeneously. We find a similar evolution of the stock markets in Bangladesh and India, and discover common elements in the reactions of the Indian and Pakistani markets. However, we can conclude that the effect of GPR on Pakistan's stock market is more pronounced. Second, the link between GPR and Sri Lankan stocks is the strongest. The relationship between GPR and the Nepali stock market is continuous and of low intensity throughout the sample period. Finaly, the level of dynamic connectedness between SAARC states was low during the analysis period.

The implications of this research for SAARC leadership, member-state governments, financial market decision-makers, and investors are as follows. First, this study provides valuable insights into the hedging, sheltering, and diversification decisions of SAARC stocks investors against the uncertainty of GPR events. We contribute to the correct substantiation of portfolio modeling decisions and the choice of risk management strategies when GPR events occur.

Second, the results are useful to governments in two ways: for limiting local GPR events and for protecting against global or regional ones. Simultaneously, the results can inform financial market authorities, enabling them to design and develop regulations to prevent capital losses and ensure investor protection. Finally, investors and portfolio managers can use the results for fund management to protect against GPR. The impact of GPR events on stock markets may enable SAARC governments to bridge political differences so that South Asia becomes a strong partner in the global economy.

Our research has certain limitations, given the size and complexity of the SAARC region. In addition, there is limited prior literature to draw upon, as most research focuses on a single state. Given the region's proximity to China, it is possible that the stock markets of the states are significantly influenced, which presents a future research direction. The lack of daily information on the Maldives over the entire sampling period affected the complete analysis.

Acknowledgments. We would like to thank Editage (www.editage.com) for English language editing.

Funding information. This research received no external funding**.**

Author contributions. Conceptualization, C.G. and O.P.; methodology, C.G. and O.P.; software, C.G. and O.P.; validation, C.G. and O.P.; formal analysis, C.G. and O.P.; investigation, C.G. and O.P.; resources, C.G. and O.P.; data curation, C.G. and O.P.; writing—original draft preparation, C.G. and O.P., writing—review and editing, C.G. and O.P.; visualization, C.G. and O.P.; supervision, C.G. and O.P.

Conflict of interest. The authors declare no conflicts of interest.

Data availability statement. The data presented in this study are available on reasonable request from the corresponding author.

References

Adeosun, O. A., Anagreh, S., Tabash, M. I., & Vo, X. V. (2024). Return and volatility transmission among economic policy uncertainty, geopolitical risk and precious metals. *Studies in Economics and Finance*. doi:10.1108/sef-10-2023-0586

Adhikary, B. K. (2017). Factors influencing foreign direct investment in South Asian economies: A comparative analysis, *South Asian Journal of Business Studies*, *6*(1), 8–37.

Agyei, S. K. (2023) Emerging markets equities' response to geopolitical risk: Time-frequency evidence from the Russian-Ukrainian conflict era. *Heliyon*, *9*(2), e13319

Ahmed, S., & Hussain, S. M. (2014) The financial cost of rivalry: A tale of two South Asia neighbors. *Emerging Market Finance and Trade*, *50*(suppl. 3), 35–60.

Ahmed, Q. N., Rizvi, S. A. A., Naeem, H. A., & Ahmed, S. (2023). Is oil prices volatility taking toll: Sectoral analysis of Pakistan Stock Exchange. *Journal of Organisational Studies & Innovation*, *10*(3), 1–16.

Antonakakis, N., Chatziantoniou, I., & Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. *Energy Economics*, *44*, 433–447.

Antonakakis, N., & Gabauer, D. (2017). Refined measures of dynamic connectedness based on TVP-VAR. Germany: University Library of Munich.

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*, 84. doi:10.3390/jrfm13040084

Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. *Finance Research Letters*, *18*, 136–141.

Arya, V., & Singh, S. (2022). Dynamics of relationship between stock markets of SAARC countries during COVID-19 pandemic. *Journal of Economic and Administrative Sciences*. doi:10.1108/JEAS-10-2021-0213

Aslam, F., Kang, H. -G., Mughal, K. S., Awan, T. M., & Mohmand, Y. T. (2021). Stock market volatility and terrorism: New evidence from the Markov switching model. *Peace Economics, Peace Science and Public Policy*, *27*(2), 263–284.

Aysan, A. F., Demir, E., Gozgor, G., & Lau, C. K. M. (2019). Effects of the geopolitical risks on Bitcoin returns and volatility. *Research in International Business and Finance*, *47*, 511–518.

Aysan, A. F., Muğaloğlu, E., Polat, A. Y., & Tekin, H. (2023). Whether and when did bitcoin sentiment matter for investors? Before and during the COVID-19 pandemic. *Financial Innovation*, *9*, 124. doi:10.1186/s40854-023-00536-9

Aziz, T., Marwat, J., Mustafa, S., Zeeshan, A., & Iqbal, Y. (2021). Linkage between US financial uncertainty and stock markets of SAARC Countries. *The Journal of Asian Finance, Economics and Business*, *8*(2), 747–757.

Bloomfield, D. S., McAteer, R. J., Lites, B. W., Judge, P. G., Mathioudakis, M., & Keenan, F. P. (2004). Wavelet phase coherence analysis: Application to a quiet-sun magnetic element. *The Astrophysical Journal*, *617*, 623–632.

Bouri, E., Shahzad, S. J. H., Roubaud, D., Kristoufek, L., & Lucey, B. (2020). Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, *77*, 156–164.

Böyükaslan, A., Demirer, R., Ergüney, E. B., & Gursoy, S. (2024). Geopolitical risks and the energy-stock market nexus: Evidence from Turkiye. *Borsa Istanbul Review*, *24*(1), 73–83.

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, *61*(1), 3–18.

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review*, *112*(4), 1194–1225.

Chaudhry, N., Roubaud, D., Akhter, W., & Shahbaz, M. (2018). Impact of terrorism on stock markets: Empirical evidence from the SAARC region. *Finance Research Letters*, *26*, 230–234.

Chaudhary, P. (2021). Impact of board structure, board activities and institutional investors on the firm risk: Evidence from India. *Managerial Finance*, *47*(4), 506–524.

Chen, X. (2023). Are the shocks of EPU, VIX, and GPR indexes on the oil-stock nexus alike? A time-frequency analysis. *Applied Economics*, *55*(48), 5637–5652.

Chien, F., Sadiq, M., Kamran, H. W., Nawaz, M. A., Hussain, M. S., & Raza, M. (2021). Co-movement of energy prices and stock market return: Environmental wavelet nexus of COVID-19 pandemic from the USA, Europe, and China. *Environmental Science and Pollution Research*, *28*(25), 32359–32373.

Dahir, A. M., Mahat, F., Ab Razak, N. H., & Bany-Ariffin, A. N. (2018). Revisiting the dynamic relationship between exchange rates and stock prices in BRICS countries: A wavelet analysis. *Borsa Istanbul Review*, *18*(2), 101–113.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms, *Journal of Econometrics*, *182*(1), 119–134.

Ellahi, N., Kiani, A. K., Awais, M., Affandi, H., Saghir, R., & Qaim, S. (2021). Investigating the institutional determinants of financial development: Empirical evidence from SAARC countries. *Sage Open*, *11*(2), 1–10.

Elsayed, A. H., Gozgor, G., & Lau, C. K. M. (2022). Risk transmissions between bitcoin and traditional financial assets during the COVID-19 era: The role of global uncertainties. *International Review of Financial Analysis*, *81*, 102069.

Gajurel, D., & Chawla, A. (2022) International information spillovers and asymmetric volatility in South Asian stock markets. *Journal of Risk and Financial Management*, *15*(10), 471.

Gong, X., & Xu, J. (2022). Geopolitical risk and dynamic connectedness between commodity markets. *Energy Economics*, *110*, 106028.

Habiba, U. E., Peilong, S., Zhang, W., & Hamid, K. (2020). International stock markets integration and dynamics of volatility spillover between the USA and South Asian markets: Evidence from global financial crisis. *Journal of Asia Business Studies*, *14*(5), 779–794.

He, Z., & Sun, H. (2024). The time-varying and asymmetric impacts of oil price shocks on geopolitical risk. *International Review of Economics & Finance*, *91*, 942–957.

Jana, S., & Sahu, T. N. (2023). Identifying cryptocurrencies as diversifying assets and safe haven in the Indian stock market. *Asia-Pacific Financial Markets*, 1–20. doi:10.1007/s10690-023-09436-5.

Jebran, K., & Iqbal, A. (2016). Examining volatility spillover between Asian countries' stock markets. *China Financial and Economic Review*, *4*(6), 1–13.

Kaur, A., & Mittal, P. (2023). Wavelet based analysis of oil price shocks, exchange rate and stock market behaviour: Evidences from emerging markets. *OPEC Energy Review*, *47*(3), 163–175.

Khan, D., Ullah, A., Alim, W., & Haq, I-U. (2022). Does terrorism affect the stock market returns and volatility? Evidence from Pakistan's stock exchange. *Journal of Public Affairs, 20*, 22, e2304.

Khraiche, M., Boudreau, J. W., & Chowdhury, M. S. R. (2023). Geopolitical risk and stock market development. *Journal of International Financial Markets, Institutions and Money*, *88*(4), 101847.

Koop, G., & Korobilis, D. (2014). A new index of financial conditions. *European Economic Review*, *71*, 101–116. doi:10.1016/j.euroecorev.2014.07.002

Li, W., Chien, F., Waqas Kamran, H., Aldeehani, T. M., Sadiq, M., Nguyen, V. C., & Taghizadeh-Hesary, F. (2022). The nexus between COVID-19 fear and stock market volatility. *Economic Research-Ekonomska istraživanja*, *35*(1), 1765–1785.

Li, X., Tong, Y., Zhong, K., Xu, G., & Zhao, W. (2024). Geopolitical risk and foreign subsidiary performance of emerging market multinationals. *Journal of Multinational Financial Management*, *72*, 100836.

Li, Z., Hasan, M. M. & Lu, Z. (2023). Assessing financial factors for oil supply disruptions and its impact on oil supply security and transportation risks. *Environmental Science and Pollution Research, 30*, 33695–33710.

Liaqat, A., Nazir, M. S., Ahmad, I., Mirza, H. H., & Anwar, F. (2020). Do stock price bubbles correlate between China and Pakistan? An inquiry of pre- and post-Chinese investment in Pakistani capital market under China-Pakistan Economic Corridor regime. *International Journal of Finance & Economics*, *25*, 323–335.

Liu, C., Sun, X., & Li, J. (2023). Time-frequency comovements between sovereign CDS and exchange rates: The role of sentiments. *Global Finance Journal*, *56*, 100775.

Liu, T., & Shigeyuki, H. (2021). Does investor sentiment affect clean energy stock? Evidence from TVP-VAR-Based Connectedness approach. *Energies*, *14*, 3442. doi:10.3390/en14123442

Jiang, Z., & Yoon, S.-M. (2020). Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. *Energy Economics*, *90*, 104835

Johansson, A. C. (2008). Interdependencies among Asian bond markets. *Journal of Asian Economics*, *19*(2), 101–116.

Maiti, M. (2019). Is idiosyncratic risk ignored in asset pricing: Sri Lankan evidence? *Future Business Journal*, *5*(5), 1–12.

Mamman, S. O., Iliyasu, J., Ahmed, U. A., & Salami, F. (2024). Global uncertainties, geopolitical risks and price exuberance: Evidence from international energy market. *OPEC Energy Review*, *00*, 1–12.

Mensi, W., Rehman, M. U., Maitra, D., Al-Yahyaee, K. H., & Vo, X. V. (2021). Oil, natural gas and BRICS stock markets: Evidence of systemic risks and co-movements in the time–frequency domain. *Resources Policy*, *72*, 102062.

Morawakage, P. S., Nimal, P. D., & Kuruppuarachchi, D. (2019). Equity risk premium puzzle: Evidence from Indonesia and Sri Lanka. *Bulletin of Indonesian Economic Studies*, *55*(2), 239–248.

Nasir, R. M., & He, F. (2023). Do clean energy stocks and sub-sectors hedge China economic policy uncertainty: New evidence from wavelet analysis. *Journal of Cleaner Production*, *429*, 139385

Nazir, M. S., Mahmood, J., Abbas, F., & Liaqat, A. (2020). Do rational bubbles exist in emerging markets of SAARC? *Journal of Economic and Administrative Sciences*, *36*(2), 164–183

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17–29. doi:10.1016/S0165-1765(97)00214-0

Phillips, P. C., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review*, *56*(4), 1043–1078.

Prakash, S., & Kumar, S. (2014). Stock market linkages: Examining the case of emerging South Asian markets. *Pacific Business Review International*, *6*(12), 29–36.

Raheem, I. D., & Le Roux, S. (2023). Geopolitical risks and tourism stocks: New evidence from causality-in- quantile approach. *Quarterly Review of Economics and Finance*, *88*, 1–7.

Rashid, A., Javed, A., Jehan, Z., & Iqbal, U. (2022). Time-varying impacts of macroeconomic variables on stock market returns and volatility: Evidence from Pakistan. *Romanian Journal of Economic Forecasting*, *25*(3), 144–166.

Sahabuddin, M., Hassan, M. F., Tabash, M. I., Al-Omari, M. A., Alam, M. K., & Islam, F. T. (2021) Co-movement and causality dynamics linkages between conventional and Islamic stock indexes in Bangladesh: A wavelet analysis, *Cogent Business & Management*, *9*(1), 1–16.

Saud, A. S., & Shakya, S. (2020). Analysis of look back period for stock price prediction with RNN variants: A case study on banking sector of NEPSE. *Procedia Computer Science*, *167*, 788–798.

Sehgal, S., Pandey, P., Deisting, F., & McMillan, D. (2018). Time varying integration amongst the South Asian equity markets: An empirical study. *Cogent Economics & Finance*, *6*(1), 5–26.

Shafiq, S., Qureshi, S. S., & Akbar, M. (2023). Dynamic relationship of volatility of returns across different markets: Evidence from selected next 11 countries. *Journal of Economic and Administrative Sciences*. DOI:10.1108/JEAS-09-2022-0216

Shahzad, A., Azeem, M., Nazir, M. S., Vo, X. V., & Linh, N. T. M. (2021). The determinants of capital structure: Evidence from SAARC countries. *International Journal of Finance & Economics*, *26*, 6471–6487.

Singh, S., Bansal, P., & Bhardwaj, N. (2022). Correlation between geopolitical risk, economic policy uncertainty, and Bitcoin using partial and multiple wavelet coherence in P5+ 1 nations. *Research in International Business and Finance*, *63*, 101756.

Singh, V. K., & Ahmed, F. (2016). Econometric analysis of financial cointegration of least developed countries (LDCs) of Asia and the Pacific. *China Finance Review International*, *6*(2), 208–227.

Sreenu, N. (2023). Effect of exchange rate volatility and inflation on stock market returns dynamics-evidence from India. *International Journal of System Assurance Engineering and Management*, *14*(3), 836–843.

Srinivasan, P., Kalaivani, M. & Ibrahim, P. (2011). An empirical investigation of foreign direct investment and economic growth in SAARC nations. *Journal of Asia Business Studies*, 5(2), 232–248.

Torrence, C., & Compo, G. P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological Society*, *79*, 61–78.

Tran, T. B. N. (2017). Speculative bubbles in emerging stock markets and macroeconomic factors: A new empirical evidence for Asia and Latin America. *Research in International Business and Finance*, 42, 454–467.

Uddin, M. A., Hoque, M. E., & Ali, M. H. (2020). International economic policy uncertainty and stock market returns of Bangladesh: Evidence from linear and nonlinear model. *Quantitative Finance and Economics*, *4* (2), 236–251.

Umar, M., Mirza, N., Rizvi, S. K. A., & Furqan, M. (2023). Asymmetric volatility structure of equity returns: Evidence from an emerging market. *The Quarterly Review of Economics and Finance*, *87*, 330–336.

Upadhyaya, K. P., Nag, R., & Mixon Jr, F. G. (2023). Causal relationships between oil prices and key macroeconomic variables in India. *International Journal of Financial Studies*, *11*(4), 143.

Wang, Q., Zhang, C., & Li, R. (2024). Impact of different geopolitical factors on the energy transition: The role of geopolitical threats, geopolitical acts, and geopolitical risks. *Journal of Environmental Management*, *352*, 119962.

Yang, M., Zhang, Q., Yi, A., & Peng, P. (2021). Geopolitical risk and stock market volatility in emerging economies: Evidence from GARCH-MIDAS model. *Discrete Dynamics in Economic and Business Systems*, *1159358*, 1–17.

Yu, L., Li, J., Tang, L., Wang, S. (2015). Linear and nonlinear Granger causality investigation between carbon market and crude oil market: A multi-scale approach. *Energy Economics*, *51*, 300–311.

Zhao, L., Liu, W., Zhou, M., & Wen, F. (2022). Extreme event shocks and dynamic volatility interactions: The stock, commodity, and carbon markets in China. *Finance Research Letters*, *47*, 102645. doi:10.1016/j.frl.2021.102645

Ziadat, S. A., Mensi, W., & Kang, S. H., (2024). Frequency spillovers between oil shocks and stock markets of top oil-producing and -consuming economies. *Energy*, *291*, 130239.

Figure 1

Click here to access/download;Figure;Figure 1.tif

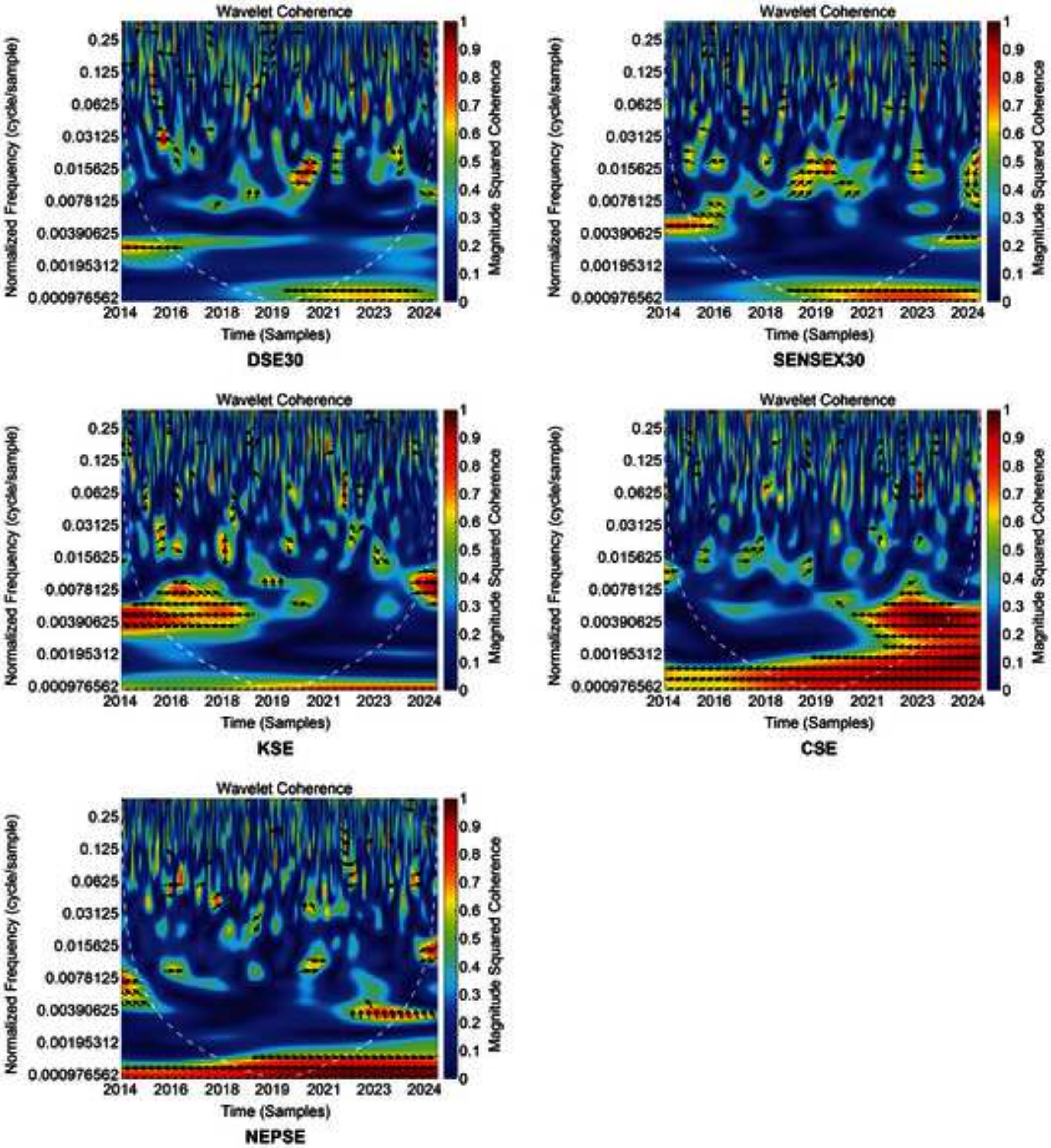


Figure 2

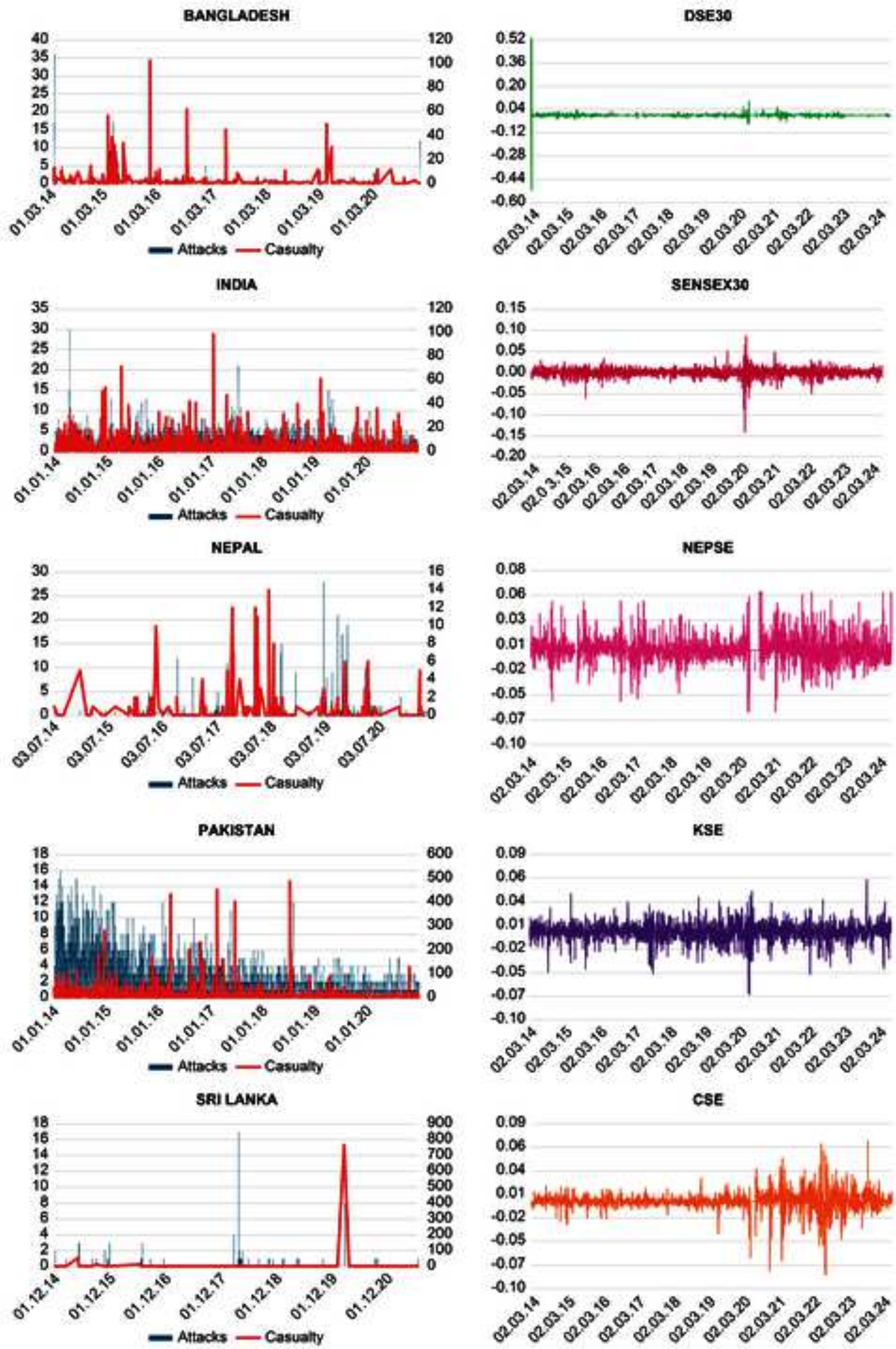

BANGLADESH
Attacks
Casualty
DSE30
INDIA
Attacks
Casualty
SENSEX30
NEPAL
Attacks
Casualty
NEPSE
PAKISTAN
Attacks
Casualty
KSE
SRI LANKA
Attacks
Casualty
CSE

Figure 3