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New insights into the role of global factors in BRICS stock markets: A quantile cointegration approach

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A B S T R A C T

Because of the acceleration in marketization and globalization, stock markets in the BRICS (Brazil, Russia, India, China, and South Africa) countries are affected by various global factors, for example, oil prices, gold prices, global stock market volatility, global economic policy uncertainty, financial stress, and investor sentiment. This paper offers new insights into the short- and long-run linkages between global factors and BRICS stock markets by applying the quantile autoregressive distributed lags (QARDL) approach. This novel methodology enables us to test short- and long-run linkages accounting for distributional asymmetry. That is, the nonlinear dynamic relationship between the global factors and BRICS stock prices depends on market conditions. Our empirical results show that the effects of gold prices and global stock market volatility on BRICS stock prices are more significant in the long run than in the short run. A decrease in global stock market volatility is associated with higher stock prices, while gold prices demonstrate upward co-movement in dynamic correlations with stock markets. Irrational factors, such as economic policy uncertainty, financial stress, and investor sentiment, play a critical role in the short term, and negative interdependence is dominant. Finally, the rolling-window estimation technique is used to examine time-varying patterns between major global factors and BRICS stock markets.

1. Introduction

Five emerging countries, namely Brazil, Russia, India, China, and South Africa (BRICS), are considered the most rapidly growing markets in the world, attracting increasing attention from scholars. This group is experiencing further integrating with developed countries, particularly in terms of investment and trade. BRICS now account for more than two-fifths of the world's population and nearly one-fifth of global gross domestic product. Moreover, the BRICS countries have become an important force that affects global politics, economics, trade, and stock markets as well as financial investment opportunities and stock market capitalization (Balcilar et al., 2018). The growing prospects of the BRICS countries give the capitalization of their stock markets great significance and affect the structure of their dependence with other stock markets (Mensi et al., 2018). However, unlike stock markets in developed countries, BRICS stock markets have the disadvantages of low information transparency, high risks, and large fluctuations. These

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characteristics attract great attention from global investors and policy makers. Because BRICS stock markets are especially vulnerable to global factors (Bouri et al., 2018; Mensi et al., 2014), a study that formally analyzes the effects of global factors on BRICS stock markets offers a new perspective on investor behavior in emerging markets, which is mostly overlooked in previous studies. Considering the potential for investment, speculation, and risk diversification, investors are following the interdependence of BRICS stock markets with these global factors with particular interest.

Interactions between international financial markets have become increasingly dominant due to increases in globalization and financial integration. Because of the risk expectation that some markets can affect prices, cash flows, and macroeconomic indicators in other markets, unanticipated shocks to both financial (e.g., the global stock market volatility) and commodity (e.g., crude oil and gold) markets, as expected, have a dominant influence on stock markets. The global stock market has played a central role in influencing the global economic system, and it has caused changes in all other markets (Zhang et al., 2019). Financial economists and investors pay attention to the daily basis of oil and gold, as they are major strategic commodities. The BRICS countries import several commodity products, such as oil (except Russia) and gold (except South Africa). The impacts of oil and gold on the stock market have become more influential than before, with the increase in the degree of financialization of these commodities. Thus these rationally economic and financial factors (oil prices, gold prices, and global stock market volatility) play a vital role in BRICS stock markets.

More importantly, uncertainties related to economic policy decisions, regardless of their causes, dampen investment behavior by individual investors, enterprises, and institutions and thus having a far-reaching impact on stock markets. Baker et al. (2016) propose an economic policy uncertainty (EPU) index to assess uncertainty regarding monetary, regulatory, fiscal, and other relevant policies, and the research suggests that the EPU affects the business cycle and investment strategies. It is generally believed that EPU has remarkable effects on stock markets (Arouri et al., 2016; Phan et al., 2018). Furthermore, an analysis of financial stress effect is necessary for oversight of the financial system. Central banks and financial institutions have created several financial stress indexes (FSI) to assess the stress conditions in financial markets and merge them into an "aggregate" stress index (Cevik et al., 2013). The application of an aggregate FSI contributes to a better evaluation of the degree of the overall financial stability in an economy or the respective financial sectors (Apostolakis, 2016; Diebold and Yılmaz, 2014). Additionally, in the past two decades, stock markets have undergone various crises, collapses, and bubbles, marked by several abnormal stylized facts. These facts challenge market efficiency and the rationality of investors. In fact, assumptions of rationality and homogeneity of agents fail to explain the anomalies and reproduce these stylized facts. Consequently, an alternative framework has emerged, resulting in an increasing number of studies regarding the behavioral finance (Lin et al., 2018; Shiller, 2003). Unlike traditional financial theory framework, behavioral finance theory confirms market inefficiency because market participants are prone to common human errors caused by heuristics and biases (Ramiah et al., 2015). This means that investors deviate from rationality, relying on their psychology in the decision-making process, and they might have different expectations of market dynamics and future events. Some researchers state that investor sentiment can explain these phenomena (Baker and Wurgler, 2006; De Long et al., 1990). They believe that investor sentiment is critical in influencing stock returns due to the unexpected demand shocks, limits of arbitrage, unbalanced specific references, and utility functions in terms of gain and loss. Since various crises and financial distresses have frequently occurred, these irrational factors related to feelings and sentiment (e.g., EPU, FSI, and investor sentiment) might become more promising in the predictors of the stock markets.

Although certain studies highlight the significance of those global factors, few have explored the effects of a broad set of global factors in a single comprehensive framework. One excellent paper on this topic is by Mensi et al. (2014). Mensi et al. (2014) employ the quantile regression method, but they focus only on the short-term relationship between global factors and BRICS stock markets while ignore the long-term dynamics. Moreover, they only study the unidirectional effects of global factors on stock markets without considering the endogeneity problem. Against this backdrop, this paper reconsiders the relationship between major global factors and BRICS stock markets by applying the QARDL model. This model, proposed by Cho et al. (2015), enables us to explore both short- and long-run dynamic relationships by considering any potential asymmetric linkages and endogeneity between global factors and BRICS stock markets. Compared to traditional cointegration analysis, this model is better in several ways. First, it considers locational asymmetry and studies the cointegration relationship between global factors and BRICS stock markets for the entire distribution, instead using the single measure of conditional central tendency. Tsong and Lee (2013) argue that traditional cointegration analysis, addressing mean behavior, cannot be informative enough. Compared to the autoregressive distributed lag (ARDL) model, the primary advantage of QARDL is that it provides a powerful technique for capturing the entire conditional distribution, thus capturing the asymmetries. Also, the QARDL model helps to directly test whether the cointegration exhibits outstanding advantages though the stock prices of BRICS countries are under different market situations (e.g., bear and bull markets). It is meaningful because investors might have different behaviors and motives under different states of the economy. Second, it relaxes the normality assumptions, thus achieving strong and convincing conclusions. Ignoring the nonnormality might result in the inability to reject the null hypothesis of no cointegration (Pierdzioch et al., 2015). Using the QARDL model, we can assess the determinants of stock prices throughout the conditional distribution, with a particular focus on bearish and bullish markets. From a policy perspective, it is more attractive to learn about what occurs at the extremes of a distribution. Therefore, the QARDL is appropriate for investigating nonlinear, asymmetric, and time-varying relationships between major global factors and BRICS stock markets.

The paper makes three contributions to the literature. First, to the best of our knowledge, this study is the first to investigate the short- and long-term nexus between global factors and BRICS stock markets. Unlike nonquantile linkages, the quantile-specific approach can take any potential asymmetric and nonlinear properties of global factors and BRICS stock markets into account.[1] It is

[1] The "nonlinear" relation here is the asymmetric linkage between the predictor variables and the response variable across various quantiles. As another important kind of nonlinear relation, volatility clustering is a well-known property of financial data. In future research, our empirical

more interesting to understand what occurs in extreme market environments. Second, although the roles of rational factors have aroused wide concern among scholars, the effects of irrational factors are often ignored. Because of the increasing concern about the impact of investor sentiment, it is essential to include not only rational factors but also irrational factors. Following Qadan and Nama (2018), we divide global factors into two categories: rational and irrational. The rational factors are oil prices, gold prices, and global stock market volatility, whereas the irrational factors are EPU, FSI, and investor sentiment. We take these six major factors into account simultaneously, which addresses the issue of gaps about variable bias problems in the existing literature. Third, we confirm whether the dependence structure is static or time varying using the rolling-estimation technique and conduct Wald tests to check for asymmetry. Our empirical findings provide useful references for investors in making investment decisions, as well as for policy makers in designing market regulations.

The structure of this paper is organized as follows. Section 2 reviews the literature. Section 3 presents the econometric methodology and describes the data. Section 4 discusses the findings, and Section 5 concludes.

2. Literature review

Not only have BRICS stock markets become more important but the capital markets in BRICS countries have received more inflows of international funds because global investors are constantly looking for attractive assets to add alternative class investments to their portfolios (Cheng et al., 2007; Ghosh et al., 2009). Bhar and Nikolova (2009) believe that BRICS stock markets are valuable for diversifying international portfolios. Recently, numerous studies have investigated the factors that affect BRICS stock markets to understand their interactions among themselves or with other stock markets. Kocaarslan et al. (2019) focus on the impact of global financial stress and nonfinancial markets on financial contagion between BRICS and the US stock markets, as various investment and risk management decisions require knowledge of these global factors. Therefore, international investors are particularly interested in the BRICS stock markets' comovements with global factors, given that investment, speculation, and risk diversification opportunities could emerge.

Several scholars have provided evidence of increasing interdependence between stocks and commodity markets, as these markets are influenced by certain common drivers of the financialization of commodity markets (Pal and Mitra, 2019). In view of the vital role played by BRICS countries in promoting world commodity markets, one strand of the literature concerns the linkages between BRICS stock markets and commodity markets, particularly oil and gold. Salisu and Gupta (2021) employ a GARCH–MIDAS (Generalized Autoregressive Conditional Heteroskedasticity variant of Mixed Data Sampling) model to explore the heterogeneous response of stock market volatility in the BRICS countries to four types of oil shocks. They argue that variation in the responses across the BRICS could be attributed to differences in the size of their economies, oil production, consumption profile, market share distribution across firms, and financial system and regulation efficiency. In addition, another strand of the literature considers the linkages between BRICS stock markets and the global stock market. Jin and An (2016) reveal that the US and the BRICS stock markets interact, and contagion effects spread from the US to the BRICS stock markets during the global financial crisis, though the intensity of effects varies.

The practical evolution in international financial markets demonstrates that EPU, FSI, and investor sentiment could be more promising predictors in the event of frequent crises and financial distresses (Gupta et al., 2014; You et al., 2017a). Brogaard and Detzel (2015) provide evidence that EPU not only plays an important role in the business cycle of financial markets but also spreads stress to other sectors of economy. Dakhlaoui and Aloui (2016) explore the correlations between EPU and BRICS stock markets, and they find that linkages between them strengthen when BRICS economies have poor conditions. FSI, as a representative proxy for the state of financial risk, affects investment activities in several ways. Financial pressure is generally interpreted as overall stress that increases with expected financial losses, risks, or uncertainties, and the current instability, as with systemic risk (Illing and Liu, 2006). A good understanding of the state of financial stress is conducive to optimization of the design and implementation of policies, and FSI can provide useful information for regulating economic policies (Cevik et al., 2016). In addition, previous studies have confirmed that investor sentiment plays an essential role in financial markets. The theory presented by De Long et al. (1990) divides stock market participants into rational and noise traders. They believe that stock prices include the fundamental value established by rational investors, and the risk premium created by noise traders. Some scholars argue that investor sentiment is critical for influencing stock markets because of the limitations of arbitrage, unexpected demand shocks, unbalanced specific references, and utility functions in gain and loss (Kahneman and Tversky, 1979).

Based on the foregoing, the nexus between the stock markets and global factors, such as the commodity markets, global stock market volatility, EPU, FSI, and investor sentiment, has been examined in previous studies. However, these major global factors have not been integrated into a comprehensive framework to analyze their impact on BRICS stock markets. Furthermore, some studies find no evidence of cointegration among these variables, applying traditional econometric approaches, for instance, the linear ARDL model and the Johansen cointegration test. Mensi et al. (2014) employ the quantile regression method and focus on the short-term relationship between global factors and BRICS stock markets. We extend the literature by employing a recent QARDL model. To the best of our knowledge, no prior paper simultaneously accounts for short- and long-run relationships by considering any potential asymmetric links between these major global factors and stock markets. The emergence of the QARDL model can address this issue effectively, because it is better for exploring short- and long-run relationships under different market conditions, such as financial crises and bubble-like periods.

(*footnote continued*)
analysis can be extended in this direction. Special thanks to an anonymous referee for this valuable suggestion.

3. Econometric methodology and data

3.1. Econometric methodology

The empirical analysis adopted in this paper is based on the QARDL model proposed by Cho et al. (2015). This model tests for the existence of asymmetric effects in short- and long-run relationships among variables of interest. As indicated earlier, it offers a good framework for exploring the information transmission mechanism from global factors to stock markets in the short and long run.

The QARDL model is a quantile extension of the linear ARDL cointegration model. The ARDL model is written as follows:

$$
\begin{aligned}
y_t \; = \; & \alpha + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=0}^{q_1} \lambda_i WTI_{t-i} + \sum_{i=0}^{q_2} \sigma_i GEPU_{t-i} + \sum_{i=0}^{q_3} \pi_i Gold_{t-i} \\
& + \sum_{i=0}^{q_4} \varphi_i Sentiment_{t-i} + \sum_{i=0}^{q_5} \omega_i FSI_{t-i} + \sum_{i=0}^{q_6} \theta_i VIX_{t-i} + \varepsilon_t
\end{aligned} \tag{1}
$$

where y_t refers to the logarithm of stock prices of BRICS countries, ε_t is the error term, WTI_t, $GEPU_t$, $Gold_t$ and VIX_t refer to logarithm of WTI crude oil prices, global economic policy uncertainty, gold prices, and global stock market volatility, respectively. FSI_t is financial stress and $Sentiment_t$ is investor sentiment. The ARDL model has several advantages for examining cointegration between time series with different orders of integration, as it enables a combination of I(0) and I(1) series. And it offers a comprehensive framework for estimating short- and long-run parameters simultaneously. Moreover, the ARDL model can be used even if the independent variables are endogenous (Pesaran et al., 2001).

Cho et al. (2015) extend the idea of quantile cointegration proposed by Koenker and Xiao (2006) in developing the QARDL model, which can simultaneously capture short- and long-run dynamics across the conditional distribution of the dependent variable. The QARDL model has several advantages over ARDL and quantile regression methods. Although the ARDL model considers the cointegration relationship among variables, it captures only linear relationships. The quantile regression model accounts for locational asymmetry because the relationships might rest with the location of the dependent variable within its conditional distribution, while ignoring the possible cointegration among variables. Specifically, the extension of the model in Eq. (1) to a quantile context leads to the following form of the QARDL (p, q) model:

$$
\begin{aligned}
y_t \; = \; & \alpha(\tau) + \sum_{i=1}^{p} \phi_i(\tau) y_{t-i} + \sum_{i=0}^{q_1} \lambda_i(\tau) WTI_{t-i} + \sum_{i=0}^{q_2} \sigma_i(\tau) GEPU_{t-i} + \sum_{i=0}^{q_3} \pi_i(\tau) Gold_{t-i} \\
& + \sum_{i=0}^{q_4} \varphi_i(\tau) Sentiment_{t-i} + \sum_{i=0}^{q_5} \omega_i(\tau) FSI_{t-i} + \sum_{i=0}^{q_6} \theta_i(\tau) VIX_{t-i} + \varepsilon_t(\tau)
\end{aligned} \tag{2}
$$

where τ denotes the quantiles. To avoid the possible serial correlation of ε_t, the basic QARDL model can be extended as follows:

$$
\begin{aligned}
\Delta y_t \; = \; & \alpha(\tau) + \rho(\tau) y_{t-1} + \psi_{WTI}(\tau) WTI_{t-1} + \psi_{GEPU}(\tau) GEPU_{t-1} + \psi_{Gold}(\tau) Gold_{t-1} \\
& + \psi_{Sentiment}(\tau) Sentiment_{t-1} + \psi_{FSI}(\tau) FSI_{t-1} + \psi_{VIX}(\tau) VIX_{t-1} \\
& + \sum_{i=1}^{p-1} \phi_i(\tau) \Delta y_{t-i} + \sum_{i=0}^{q_1-1} \lambda_i(\tau) \Delta WTI_{t-i} + \sum_{i=0}^{q_2-1} \sigma_i(\tau) \Delta GEPU_{t-i} + \sum_{i=0}^{q_3-1} \pi_i(\tau) \Delta Gold_{t-i} \\
& + \sum_{i=0}^{q_4-1} \varphi_i(\tau) \Delta Sentiment_{t-i} + \sum_{i=0}^{q_5-1} \omega_i(\tau) \Delta FSI_{t-i} + \sum_{i=0}^{q_6-1} \theta_i(\tau) \Delta VIX_{t-i} + \upsilon_t(\tau)
\end{aligned} \tag{3}
$$

However, the error term $\upsilon_t(\tau)$ might still be likely to have a contemporaneous correlation with ΔWTI_t, $\Delta GEPU_t$, $\Delta Gold_t$, $\Delta Sentiment_t$, ΔFSI_t, and ΔVIX_t. It can be modified by using a projection of λ_* on ΔWTI_t, $\Delta GEPU_t$, $\Delta Gold_t$, $\Delta Sentiment_t$, ΔFSI_t, and ΔVIX_t:

$$
\upsilon_t = \gamma_{WTI} \Delta WTI_t + \gamma_{GEPU} \Delta GEPU_t + \gamma_{Gold} \Delta Gold_t + \gamma_{Sentiment} \Delta Sentiment_t + \gamma_{FSI} \Delta FSI_t + \gamma_{VIX} \Delta VIX_t + \varepsilon_t \, ,
$$

where ε_t is uncorrelated with ΔWTI_t, $\Delta GEPU_t$, $\Delta Gold_t$, σ_*, ΔFSI_t, andΔVIX_t. Incorporating the previous projection into Eq. (3) and generalizing it in the quantile regression framework, we obtain the following QARDL-ECM model:

$$
\begin{aligned}
\Delta y_t \; = \; & \alpha(\tau) + \rho(\tau)(y_{t-1} - \beta_{WTI}(\tau) WTI_{t-1} - \beta_{GEPU}(\tau) GEPU_{t-1} - \beta_{Gold}(\tau) Gold_{t-1} \\
& - \beta_{Sentiment}(\tau) Sentiment_{t-1} - \beta_{FSI}(\tau) FSI_{t-1} - \beta_{VIX}(\tau) VIX_{t-1}) \\
& + \sum_{i=1}^{p-1} \phi_i(\tau) \Delta y_{t-i} + \sum_{i=0}^{q_1-1} \lambda_i(\tau) \Delta WTI_{t-i} + \sum_{i=0}^{q_2-1} \sigma_i(\tau) \Delta GEPU_{t-i} + \sum_{i=0}^{q_3-1} \pi_i(\tau) \Delta Gold_{t-i} \\
& + \sum_{i=0}^{q_4-1} \varphi_i(\tau) \Delta Sentiment_{t-i} + \sum_{i=0}^{q_5-1} \omega_i(\tau) \Delta FSI_{t-i} + \sum_{i=0}^{q_6-1} \theta_i(\tau) \Delta VIX_{t-i} + \upsilon_t(\tau)
\end{aligned} \tag{4}
$$

where $\beta_{WTI} = -\psi_{WTI}/\rho$, $\beta_{GEPU} = -\psi_{GEPU}/\rho$, $\beta_{Gold} = -\psi_{Gold}/\rho$, $\beta_{Sentiment} = -\psi_{Sentiment}/\rho$, $\beta_{FSI} = -\psi_{FSI}/\rho$, and $\beta_{VIX} = -\psi_{VIX}/\rho$. In particular, this paper focuses on the parameters as follows: (1)ρ: the coefficient of error correction term (ECM), denoting the adjustment speed toward the long-run equilibrium between BRICS stock prices and global factors; (2) β_{WTI}, β_{GEPU}, β_{Gold}, $\beta_{Sentiment}$, β_{FSI} and

β_{VIX}: the long-run cointegrating coefficients; (3) $\phi_* = \sum_{i=1}^{p-1} \phi_i$: the cumulative short-run effects of past variations of stock prices on the current variations of stock prices; and (4) $\lambda_* = \sum_{i=0}^{q_1-1} \lambda_i$, $\sigma_* = \sum_{i=0}^{q_2-1} \sigma_i$, $\pi_* = \sum_{i=0}^{q_3-1} \pi_i$, $\varphi_* = \sum_{i=0}^{q_4-1} \varphi_i$, $\omega_* = \sum_{i=0}^{q_5-1} \omega_i$ and $\theta_* = \sum_{i=0}^{q_6-1} \theta_i$: the cumulative short-run effects of contemporaneous and past variations in crude oil prices, EPU, gold prices, investor sentiment, FSI, and global stock market volatility on the current variations of stock prices. The conventional delta method can be used to estimate the cumulative short- and long-run coefficients.

To further study the short- and long-run asymmetric effects of global factors on stock prices in BRICS countries, we conduct the Wald test. This test asymptotically follows a chi-squared distribution and is often employed to test the null hypothesis of parameter constancy across quantiles. For example, this paper examines whether the adjustment speed $\rho(\tau)$ is quantile dependent. Following Shahbaz et al. (2018), we test the following null hypotheses:

H_0: $\rho(0.05) = \rho(0.5)$ and H_0: $\rho(0.05) = \rho(0.5)$

The same hypotheses are tested for the long-run cointegration parameters (β_{WTI}, β_{GEPU}, β_{Gold}, $\beta_{Sentiment}$, β_{FSI} and β_{VIX}) and the cumulative short-run parameters (φ_*, λ_*, σ_*, π_*, ϕ_*, ω_* and θ_*). The rejection of the null hypothesis indicates that the effects of global factors on BRICS stock prices are asymmetric across quantiles.

3.2. Data sources and summary statistics

This paper investigates the co-movement patterns between the BRICS stock markets and major global factors based on monthly data over the period September 1997 to December 2018. The sample is chosen based on data availability. The major global factors are as follows. The world crude oil price is represented by WTI Spot Price FOB (dollars per barrel), which is regarded as a global crude oil price benchmark (Reboredo, 2013). This index is collected from the Energy Information Administration (EIA) and adjusted by the United States (US) Producer Price Index (PPI) to obtain real oil prices. The gold price, expressed in US dollars per ounce, is collected from the World Gold Council and deflated by the US consumer price index (CPI). The global stock market volatility (VIX), represented by the implied volatility of the S&P 500 index, is obtained from Yahoo Finance. The global EPU index proposed by Baker et al. (2016) is used. Baker's EPU index is acknowledged as a good measure of true economic policy uncertainty and is widely applied to policy issues across a range of factors, such as fiscal, monetary, regulatory, tax, international trade, and political and economic change (Shahzad et al., 2017; You et al., 2017b). The financial stress index, published by the Federal Reserve Bank of St. Louis is constructed based on seven interest rate series, six yield spreads, and five other financial series (Kliesen and Smith, 2010).[2] The investor sentiment index[3] published by Huang et al. (2015) summarizes information from six representative indicators, namely, the closed-end fund discount rates, share turnover, the number of initial public offerings (IPOs), first-day returns of IPOs, the dividend premium, and newly issued equity shares. The selection of these global factors depends on their interdependence with stock market performance in the BRICS. The stock prices are converted to national currencies and then deflated by their national CPI. These major global factors are divided into two categories: rational factors (crude oil prices, gold prices, and VIX) and irrational factors (EPU, FSI, and investor sentiment index). All variables, except FSI and investor sentiment, are converted into logarithmic forms.

Table 1 gives a basic summary of the variables, showing that the standard deviation ranges from 0.133 to 0.955. The stock price in Russia, the investor sentiment index, and FSI have higher variability. The skewness in all the series, except the gold price and EPU, does not equal zero, indicating that the distribution of all the variables is asymmetrical. The kurtosis of all series except *China_stock*, *Russia_stock*, *FSI* and *Sentiment* is less than 3. The D'Agostino (1970) tests for skewness all exceed their critical values except the gold price and the EPU. The Anscombe and Glynn (1983) tests for kurtosis all exceed their critical values, except the VIX. The QARDL model can deal with a mixture of I(0) and I(1) variables, but a higher order is not allowed (e.g., I(2)). Thus, we use the augmented Dickey-Fuller (ADF) statistic to test for stationarity before estimating the QARDL model. The results, given in Table 1, confirm that the variables selected are I(0) or I(1), and none of the variables is I(2), which confirms the appropriateness of the QARDL method. Finally, it is important to test for the degree of persistence in the variables, so we perform a persistence test, regressing a first-order autoregressive process for the predictor using an ordinary least squares estimator. The estimated AR (1) coefficients reported in Table 1 are significant and close to one. Additionally, we use the VIF to test whether the six variables in our model have multicollinearity. The value of VIF is 2.41, which is less than 10, so the model has no multicollinearity.

4. Empirical results and discussion

This section empirically explores how major global factors influence the BRICS stock markets. The linear ARDL (p,q) model in Eq. (1) is estimated first. Specifically, the Schwarz information criterion (SIC) is used to ascertain the optimal lag orders p and q_1, q_2, q_3, q_4, q_5, and q_6. Then, we to use the portion of the ARDL (p,q) corresponding to quantiles in order to apply the QARDL method. The QARDL method enables a better understanding of the dynamic short- and long-run correlations between the major global factors and BRICS stock markets by revealing potential heterogeneous relationships. Considering the structural break date of the dependent variables, we included the financial crisis of 2008, as a dummy variable in the QARDL model. A large body of literature suggests that the global financial crisis had a significant influence on the stock market as well as other markets, such as oil and exchange rate markets (e.g., Berger and Uddin, 2016; Chiang et al., 2007; Reboredo and Ugolini, 2016; Sun et al., 2020; Wen et al., 2012). For this

[2] https://research.stlouisfed.org/fred2/series/STLFSI/downloaddata/.

[3] Huang et al. (2015) published the index data at "http://apps.olin.wustl.edu/faculty/zhou".

Table 1
Summary statistical properties for BRICS stock prices and global factors.

	Brazil_stock	China_stock	India_stock	Russia_stock	SA_stock	Oil	Gold	VIX	EPU	FSI	Sentiment
Mean	4.622	3.378	4.169	4.499	4.412	1.771	2.888	1.280	2.022	0.199	-0.195
Max	4.954	3.834	4.498	4.865	4.668	2.125	3.264	1.777	2.438	4.621	2.397
Min	4.189	3.120	3.760	3.196	3.957	1.266	2.526	0.978	1.713	-1.381	-1.332
Std.Dev	0.183	0.133	0.201	0.309	0.205	0.188	0.231	0.155	0.166	0.955	0.689
Skewness	-0.394**	0.579***	-0.562***	-1.920***	-0.463***	-0.475***	-0.163	0.423***	0.234	0.910***	1.696***
	(−2.561)	(3.635)	(−3.543)	(−8.872)	(−2.970)	(−3.041)	(−1.089)	(2.734)	(1.553)	(5.313)	(8.230)
Kurtosis	2.317***	3.678**	1.931***	6.672***	1.685***	2.527*	1.495	2.847	2.355***	5.654***	5.425***
	(−3.260)	(1.985)	(−7.997)	(5.279)	(−17.241)	(−1.853)	(NA)	(−0.342)	(−2.967)	(4.536)	(4.334)
ADF(level)	0.479	0.258	0.741	0.930	1.079	-0.021	1.101	-0.567	0.448	-2.501**	-2.281**
ADF(△)	-15.846***	-14.228***	-14.922***	-14.503***	-16.108***	-12.418***	-17.899***	-19.169***	-12.324***	-13.773***	-14.660***
Persistence test	0.980***	0.963***	0.990***	0.978***	0.991***	0.979***	0.995***	0.850***	0.900***	0.965***	0.954***

Notes: (1) Brazil_stock, China_stock, India_stock, Russia_stock, and SA_stock denote the stock price of Brazil, China, India, Russia, and South Africa, respectively. (2) All the variables in our model are transformed into logarithm form except financial stress index and investor sentiment index. (3) ADF is the augmented Dickey Fuller test. They are adopted to test the unit root in the series. (4) Figures in parentheses below the skewness are the test statistic for the D'Agostino (1970) test for skewness in normally distributed data. Figures in parentheses below the kurtosis are the test statistic for the Anscom and Glynn, 1983 test for kurtosis, NA denotes Not Available. The null hypothesis the data obey a normal distribution. (5) ***, ** and * denote statistical significance at the 1%, 5%and 10% levels, respectively.

reason, we use September 2008, when Lehman filed for bankruptcy, as the break point.[4] Following Pata and Caglar (2021), we add a dummy variable to the QARDL model (Eq. (4)), which equals 1 if the data are from September 2008 to December 2018, and 0 otherwise.[5] The results of quantile estimations are in Tables 2–6. We report the results for eleven quantiles (5th, 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, 90th, and 95th) to represent various market statuses. Standard errors are calculated using a stationary bootstrap with random block lengths.[6]

4.1. Relationships between BRICS stock markets and commodity markets

Table 2 displays the results for Brazil's market. The ECM parameter ρ varies with quantiles and is insignificantly negative in six of the eleven quantiles. β_{WTI} and β_{Gold} are insignificant at all quantiles, indicating that these two commodity markets have no long-run equilibrium with the Brazilian stock market. With respect to the short-run dynamics, the cumulative short-run effect of gold prices on the Brazilian stock market is significantly positive at all quantiles (except the 80th).

For China (Table 3), the ECM parameter ρ is significantly negative at most quantiles. Gold prices have a long-run equilibrium with the stock market at extremely low quantiles, as β_{Gold} is significantly positive at the 5th quantile. The cumulative short-run impact of gold prices on the Chinese stock market is significantly positive at low and intermediate quantiles. The crude oil market has no long-run equilibrium with the stock market, as β_{WTI} is insignificant across quantiles. The cumulative short-run impact of oil prices on the Chinese stock market is also negligible at all quantiles except the 95th.

For India (Table 4), the ECM parameter ρ is significantly negative at all quantiles except the 30th. No evidence supports a short- or long-run relationship between oil prices and the Indian stock market as λ_* and β_{WTI} is insignificant at all quantiles. The gold market has a significantly and positively cumulative short-run effect on the Indian stock market at most quantiles.

For Russia (Table 5), the ECM parameter ρ is significantly negative at high quantiles. The short- and long-run relationship between oil prices and the Russian stock market is also negligible at all quantiles. The gold market has significantly positive upper-tail dependence on the Russian stock market in the long run. Moreover, the cumulative influence of gold prices on the Russian stock market is significantly positive at low and high quantiles in the short run.

For South Africa (Table 6), the ECM parameter ρ is significantly negative at most quantiles. No evidence supports a short- or long-run relationship between oil prices and the South African stock market, as λ_* and β_{WTI} are insignificant across quantiles. However, the cumulative impact of contemporaneous and prior changes in gold prices on the South African stock market is significantly positive across quantiles. The gold market has a significantly and positive long-run effect on the South African stock market at all quantiles except those that are extremely low and extremely high.

In general, the estimation results for the BRICS countries are heterogeneous, depending on the countries' characteristics, and have quantile-varying properties. Oil prices mostly have insignificantly symmetric dependence on BRICS stock prices, whereas gold prices co-move with BRICS stock prices in both the short and long run (except Brazil and India in the long run), and the dependence pattern is asymmetric in China only in short term. Baur and Lucey (2010) argue that an asset can be considered a hedge if it is uncorrelated or negatively correlated with another asset. Our findings lead to the conclusion that oil can serve as a hedge and act as a safe haven for all BRICS countries, and this suggests that hedging strategies that include BRICS stock and commodity assets can help in reducing portfolio risk.

4.2. The relationship between BRICS stock markets and global stock market volatility

Contemporaneous and prior variations in global stock market volatility significantly and negatively affect the Indian stock market at all quantiles and are similar across quantiles for China and Russia except at extremely low quantiles. For South Africa, the current and past changes in global stock prices have significantly negative impacts on current changes in South African stock prices only at medium and high quantiles. With regard to long-term linkage, global stock market volatility has no impact on the distribution of Brazilian, Chinese, Indian and Russian stock prices, as β_{VIX} is insignificant at all quantiles. But global stock market volatility has a negative long-run equilibrium with the South African stock market at all quantiles except those that are extremely high.

These results indicate that global stock market volatility has a remarkable effect on all BRICS stock markets except that of Brazil. The reason is that BRICS markets are highly integrated with the global stock market. Because of this high integration with the global market and strong correlation with non-BRICS stock markets, portfolio investors have an opportunity to obtain good returns by investing in BRICS stocks (Bouri et al., 2018). The short- and long-run stock market relationships might provide useful information for asset valuation, effective diversification, hedging, portfolio allocation, and risk control. Based on these findings, investors might find investment more attractive in Brazil than in other BRICS countries during periods of high volatility in global markets.

4.3. The relationship between BRICS stock markets and EPU, the FSI and the sentiment index

The results show that σ_* is significantly negative only at extremely high quantiles for China and Brazil, and extremely low and medium quantiles for Russia, indicating a downward trend of short-run co-movement between EPU and these stock markets. The

[4] We thank the anonymous referee for pointing out the presence of structural breaks.

[5] Considering that this paper focuses mainly on variables related to global factors, the coefficients of the dummy variable are not reported but are available from the authors on request.

[6] We thank the anonymous referee for a good suggestion regarding this point.

Table 2
QARDL estimation results for Brazil.

Coefficients	Quantile levels										
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Short-run related parameters											
φ_*	0.079	0.037	-0.345	-0.124	0.044	0.123	0.005	-0.030	-0.155	-0.252	-0.221
	(0.381)	(0.331)	(0.275)	(0.241)	(0.228)	(0.224)	(0.221)	(0.202)	(0.201)	(0.218)	(0.224)
λ_*	0.115	0.092	0.070	0.077	0.086	0.126	0.086	0.124	0.111	0.121	0.093
	(0.127)	(0.109)	(0.100)	(0.085)	(0.088)	(0.094)	(0.089)	(0.086)	(0.101)	(0.118)	(0.118)
σ_*	-0.08	-0.044	-0.031	-0.038	-0.051	-0.051	-0.059	-0.055	-0.053	-0.081*	-0.117**
	(0.058)	(0.056)	(0.048)	(0.039)	(0.036)	(0.035)	(0.038)	(0.041)	(0.045)	(0.05)	(0.055)
π_*	0.907**	1.016***	1.164***	1.052***	1.083***	1.006***	0.728**	0.570*	0.516	0.775**	0.950**
	(0.362)	(0.341)	(0.373)	(0.337)	(0.306)	(0.295)	(0.292)	(0.296)	(0.337)	(0.375)	(0.370)
ϕ_*	0.005	0.017	0.022	0.012	0.022*	0.023*	0.015	0.018	0.018	0.021	0.024
	(0.019)	(0.017)	(0.015)	(0.013)	(0.012)	(0.012)	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)
ω_*	0.001	0.003	-0.007	0.007	0.005	0.004	0.008	0.005	0.003	-0.004	-0.004
	(0.017)	(0.014)	(0.013)	(0.011)	(0.01)	(0.01)	(0.011)	(0.012)	(0.013)	(0.015)	(0.016)
θ_*	-0.177	-0.137	-0.248	-0.154	-0.14	-0.101	-0.162	-0.183	-0.069	0.016	0.021
	(0.221)	(0.183)	(0.152)	(0.127)	(0.117)	(0.124)	(0.133)	(0.130)	(0.139)	(0.158)	(0.170)
Long-run related parameters											
ρ	0.019	0.033	0.032	-0.003	-0.029	-0.030	-0.022	-0.011	-0.046	-0.054	-0.019
	(0.062)	(0.062)	(0.05)	(0.041)	(0.040)	(0.043)	(0.044)	(0.042)	(0.041)	(0.04)	(0.042)
β_{WTI}	-4.658	-1.855	-0.757	-3.980	0.004	-0.101	-0.546	-2.81	-0.241	0.356	1.300
	(16.056)	(4.306)	(2.241)	(75.284)	(1.365)	(1.52)	(2.713)	(13.191)	(0.923)	(0.601)	(2.885)
β_{GEPU}	2.104	-0.221	-0.427	-3.61	-0.609	0.018	-0.691	-0.13	-0.224	-0.093	0.490
	(7.664)	(1.362)	(1.403)	(61.017)	(1.366)	(1.07)	(1.894)	(2.874)	(0.696)	(0.604)	(2.253)
β_{Gold}	7.051	3.869	2.943	-3.274	0.201	0.110	-0.737	-0.114	-0.345	-1.211	-6.983
	(20.212)	(6.131)	(4.097)	(64.315)	(1.929)	(2.002)	(3.513)	(5.396)	(1.509)	(2.038)	(18.361)
$\beta_{Sentiment}$	0.624	0.201	0.284	-3.32	-0.204	-0.092	-0.524	-0.646	-0.212	-0.089	-0.314
	(1.824)	(0.317)	(0.384)	(55.523)	(0.393)	(0.277)	(1.162)	(2.729)	(0.294)	(0.189)	(0.951)
β_{FSI}	0.018	-0.087	0.004	0.336	-0.051	-0.039	-0.142	-0.14	-0.069	-0.045	-0.177
	(0.259)	(0.165)	(0.117)	(6.125)	(0.093)	(0.094)	(0.247)	(0.469)	(0.07)	(0.068)	(0.358)
β_{VIX}	-0.353	1.058	1.526	-10.087	-0.466	-0.754	-0.255	-1.191	0.117	-0.153	0.104
	(2.297)	(1.955)	(2.397)	(169.678)	(1.272)	(1.606)	(1.531)	(5.676)	(0.604)	(0.613)	(1.657)

Notes: Figures in parentheses are standard errors. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 3
QARDL estimation results for China.

Coefficients	Quantile levels										
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Short-run related parameters											
φ_*	0.909**	0.760**	0.403	0.388	0.502*	0.503*	0.205	0.359	0.607**	0.544*	0.463
	(0.362)	(0.336)	(0.315)	(0.302)	(0.308)	(0.307)	(0.3)	(0.286)	(0.287)	(0.307)	(0.388)
λ_*	-0.115	-0.054	-0.022	-0.006	-0.051	-0.089	-0.069	-0.126	-0.004	-0.176	-0.450*
	(0.219)	(0.179)	(0.142)	(0.135)	(0.147)	(0.17)	(0.183)	(0.183)	(0.183)	(0.209)	(0.247)
σ_*	0.006	-0.024	-0.041	-0.021	-0.017	0.001	-0.034	-0.046	-0.068*(0.039)	-0.089**	-0.056
	(0.041)	(0.038)	(0.035)	(0.035)	(0.037)	(0.041)	(0.044)	(0.041)		(0.042)	(0.051)
π_*	0.277*	0.335**	0.250**	0.225*	0.268*	0.247*	0.178	0.195	0.141	0.038	-0.181
	(0.142)	(0.134)	(0.126)	(0.124)	(0.139)	(0.15)	(0.155)	(0.153)	(0.156)	(0.171)	(0.190)
ϕ_*	-0.077***	-0.055**	-0.042**	-0.030*	-0.019	-0.024	-0.012	-0.003	-0.014	-0.0003	-0.005
	(0.023)	(0.022)	(0.018)	(0.017)	(0.016)	(0.016)	(0.017)	(0.018)	(0.022)	(0.027)	(0.031)
ω_*	0.010	0.010	0.009	0.0002	-0.004	-0.009	-0.003	-0.004	-0.005	-0.006	-0.006
	(0.012)	(0.011)	(0.009)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.014)	(0.016)
θ_*	-0.092***	-0.076**	-0.073**	-0.096***	-0.092***	-0.065*	-0.07	-0.083*	-0.01	-0.009	0.011
	(0.034)	(0.031)	(0.03)	(0.03)	(0.033)	(0.038)	(0.044)	(0.05)	(0.047)	(0.051)	(0.059)
Long-run related parameters											
ρ	-0.169***	-0.143***	-0.100***	-0.082**	-0.070*	-0.054	-0.019	-0.011	-0.037	-0.024	0.004
	(0.043)	(0.041)	(0.037)	(0.036)	(0.037)	(0.041)	(0.041)	(0.042)	(0.042)	(0.048)	(0.054)
β_{WTI}	-0.012	0.044	-0.086	-0.17	-0.169	-0.566	-1.229	-0.461	0.773	-1.136	18.239
	(0.2)	(0.206)	(0.3)	(0.373)	(0.442)	(0.69)	(2.99)	(3.244)	(1.427)	(2.864)	(246.505)
β_{GEPU}	0.385*	0.208	-0.099	-0.152	-0.141	-0.471	-3.322	-5.224	-1.23	-2.664	22.563
	(0.187)	(0.203)	(0.312)	(0.368)	(0.441)	(0.746)	(7.67)	(20.77)	(1.696)	(5.826)	(302.225)
β_{Gold}	0.581*	0.239	0.074	0.297	0.327	1.12	3.213	2.212	0.244	0.598	-15.231
	(0.305)	(0.336)	(0.519)	(0.665)	(0.821)	(1.196)	(6.455)	(7.581)	(1.639)	(2.762)	(215.748)
$\beta_{Sentiment}$	0.097**	0.073*	0.064	0.122*	0.114	0.131	0.133	-0.205	-0.101	-0.144	2.938
	(0.038)	(0.038)	(0.053)	(0.063)	(0.072)	(0.097)	(0.288)	(1.205)	(0.255)	(0.54)	(38.82)
β_{FSI}	-0.028	-0.019	-0.044	-0.075*	-0.106*	-0.078	-0.212	-0.381	-0.197	-0.140	0.041
	(0.019)	(0.023)	(0.029)	(0.045)	(0.064)	(0.083)	(0.425)	(1.325)	(0.2)	(0.234)	(1.803)
β_{VIX}	-0.228	-0.154	-0.13	-0.251	-0.225	-0.196	1.125	2.522	1.547	1.216	-6.952
	(0.215)	(0.228)	(0.264)	(0.304)	(0.366)	(0.54)	(2.492)	(9.243)	(1.699)	(2.084)	(99.583)

Notes: Figures in parentheses are standard errors. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 4
QARDL estimation results for India.

Coefficients	Quantile levels										
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Short-run related parameters											
φ_*	0.157	0.168	-0.033	-0.028	0.045	0.067	-0.024	0.033	0.071	0.003	0.032
	(0.166)	(0.156)	(0.108)	(0.086)	(0.078)	(0.079)	(0.091)	(0.1)	(0.096)	(0.101)	(0.099)
λ_*	0.054	0.036	0.114	0.046	0.065	0.025	-0.007	0.042	0.066	0.041	0.128
	(0.149)	(0.133)	(0.1)	(0.079)	(0.072)	(0.073)	(0.068)	(0.07)	(0.068)	(0.068)	(0.08)
σ_*	-0.006	-0.025	-0.039	-0.044	-0.02	-0.011	-0.02	-0.037	-0.024	-0.041	0.001
	(0.045)	(0.035)	(0.032)	(0.031)	(0.033)	(0.032)	(0.032)	(0.033)	(0.036)	(0.042)	(0.05)
π_*	0.298*	0.225	0.197	0.212*	0.160	0.212**	0.207	0.139	0.142	0.374**	0.389**
	(0.174)	(0.16)	(0.138)	(0.124)	(0.114)	(0.108)	(0.109)	(0.121)	(0.14)	(0.168)	(0.173)
ϕ_*	-0.012	-0.002	0.005	-0.001	-0.01	-0.007	-0.009	-0.006	-0.01	-0.004	0.006
	(0.02)	(0.016)	(0.012)	(0.013)	(0.014)	(0.014)	(0.013)	(0.011)	(0.009)	(0.01)	(0.012)
ω_*	-0.018	0.007	0.028	0.026	0.019	0.018	0.015	0.011	0.019	0.049**	0.054**
	(0.034)	(0.025)	(0.019)	(0.017)	(0.016)	(0.015)	(0.016)	(0.018)	(0.019)	(0.022)	(0.023)
θ_*	-0.162***	-0.161***	-0.104***	-0.096***	-0.118***	-0.133***	-0.128***	-0.111***	-0.120***	-0.125***	-0.145***
	(0.049)	(0.042)	(0.036)	(0.035)	(0.033)	(0.03)	(0.026)	(0.024)	(0.023)	(0.025)	(0.029)
Long-run related parameters											
ρ	-0.074*	-0.083**	-0.088**	-0.061	-0.076*	-0.077**	-0.063**	-0.061**	-0.058**	-0.072**	-0.070**
	(0.044)	(0.041)	(0.041)	(0.044)	(0.04)	(0.033)	(0.03)	(0.026)	(0.026)	(0.029)	(0.034)
β_{WTI}	0.472	0.06	0.072	0.129	0.281	0.356	0.376	0.356	0.256	-0.259	-0.133
	(0.608)	(0.456)	(0.392)	(0.5)	(0.379)	(0.384)	(0.497)	(0.534)	(0.492)	(0.448)	(0.441)
β_{GEPU}	-0.808	-0.789*(0.469)	-0.534	-0.502	-0.141	-0.247	-0.242	-0.238	-0.432	-0.737*	-0.525
	(0.666)		(0.373)	(0.561)	(0.41)	(0.319)	(0.344)	(0.331)	(0.405)	(0.402)	(0.399)
β_{Gold}	0.138	0.755	0.619	0.999	0.667	0.427	0.359	-0.003	-0.107	0.538	0.557
	(1.146)	(0.812)	(0.701)	(0.873)	(0.628)	(0.578)	(0.684)	(0.774)	(0.774)	(0.639)	(0.691)
$\beta_{Sentiment}$	-0.04	-0.064	-0.113	-0.181	-0.123	-0.139	-0.125	-0.148	-0.211*	-0.140*	-0.144
	(0.105)	(0.082)	(0.08)	(0.151)	(0.089)	(0.093)	(0.11)	(0.109)	(0.118)	(0.081)	(0.094)
β_{FSI}	-0.059	-0.021	-0.051	-0.064	-0.084**	-0.101***	-0.124**	-0.111**	-0.129**	-0.069*	-0.089*
	(0.085)	(0.061)	(0.041)	(0.05)	(0.038)	(0.037)	(0.053)	(0.053)	(0.054)	(0.041)	(0.053)
β_{VIX}	-0.963	-0.769	-0.539	-0.731	-0.493	-0.275	-0.317	0.209	0.334	0.373	0.498
	(0.776)	(0.55)	(0.356)	(0.551)	(0.349)	(0.307)	(0.388)	(0.438)	(0.408)	(0.337)	(0.445)

Notes: Figures in parentheses are standard errors. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 5
QARDL estimation results for Russia.

Coefficients	Quantile levels										
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Short-run related parameters											
φ_*	0.154	0.139	-0.179	0.044	-0.067	0.033	0.204	0.235	0.075	0.357	0.182
	(0.378)	(0.356)	(0.307)	(0.313)	(0.318)	(0.332)	(0.303)	(0.277)	(0.264)	(0.25)	(0.256)
λ_*	0.036	0.043	-0.021	0.04	0.106	0.086	0.008	0.032	0.088	0.058	0.031
	(0.16)	(0.125)	(0.098)	(0.096)	(0.097)	(0.098)	(0.099)	(0.099)	(0.101)	(0.104)	(0.104)
σ_*	-0.174**	-0.138**	-0.058	-0.049	-0.048	-0.070*	-0.067	-0.059	-0.058	-0.033	-0.029
	(0.08)	(0.059)	(0.044)	(0.04)	(0.04)	(0.042)	(0.044)	(0.045)	(0.05)	(0.044)	(0.045)
π_*	-0.041	0.154	0.336*	0.240	0.219	0.219	0.216	0.321**	0.264*	0.249	0.217
	(0.243)	(0.213)	(0.184)	(0.171)	(0.167)	(0.167)	(0.161)	(0.157)	(0.158)	(0.162)	(0.161)
ϕ_*	0.012	-0.018	0.005	0.010	-0.006	-0.001	-0.001	-0.014	-0.017	-0.015	-0.008
	(0.028)	(0.025)	(0.021)	(0.019)	(0.018)	(0.018)	(0.019)	(0.019)	(0.017)	(0.015)	(0.015)
ω_*	0.014	0.018	0.005	0.004	0.004	0.002	0.001	-0.0003	0.002	-0.001	-0.0004
	(0.027)	(0.02)	(0.013)	(0.012)	(0.011)	(0.011)	(0.01)	(0.009)	(0.009)	(0.01)	(0.011)
θ_*	-0.142**	-0.151***	-0.157***	-0.109***	-0.095**	-0.111***	-0.110***	-0.091**	-0.079*	-0.045	-0.058
	(0.065)	(0.056)	(0.044)	(0.041)	(0.041)	(0.04)	(0.038)	(0.038)	(0.04)	(0.045)	(0.049)
Long-run related parameters											
ρ	0.049	0.036	0.040	0.007	0.004	-0.004	-0.05	-0.099*	-0.126**	-0.162***	-0.174***
	(0.05)	(0.046)	(0.043)	(0.043)	(0.046)	(0.051)	(0.052)	(0.053)	(0.049)	(0.043)	(0.04)
β_{WTI}	0.738	0.564	0.863	5.918	6.499	-6.314	-0.356	0.021	0.246	-0.021	-0.039
	(1.359)	(1.499)	(1.367)	(34.026)	(83.784)	(78.903)	(0.932)	(0.383)	(0.288)	(0.235)	(0.255)
β_{GEPU}	-0.049	0.959	-0.502	1.691	7.226	-5.925	-0.522	-0.357	-0.485*	-0.410**	-0.411**
	(1.288)	(1.943)	(1.143)	(11.149)	(96.367)	(70.779)	(0.713)	(0.307)	(0.264)	(0.19)	(0.191)
β_{Gold}	1.042	1.41	0.366	-4.823	4.179	-3.597	0.297	0.543	0.037	0.561*	0.623**
	(1.957)	(2.187)	(1.918)	(34.532)	(46.307)	(56.55)	(1.291)	(0.569)	(0.521)	(0.337)	(0.323)
$\beta_{Sentiment}$	0.200	0.338	-0.017	0.311	2.379	-1.185	-0.193	-0.085	-0.112*	-0.104**	-0.075**
	(0.341)	(0.526)	(0.2)	(2.256)	(32.232)	(13.806)	(0.2)	(0.063)	(0.055)	(0.046)	(0.043)
β_{FSI}	-0.008	-0.058	-0.138	-0.267	-0.637	0.215	0.006	-0.011	-0.007	-0.024	-0.024
	(0.11)	(0.135)	(0.154)	(1.4)	(7.909)	(3.147)	(0.075)	(0.032)	(0.026)	(0.019)	(0.02)
β_{VIX}	-0.012	0.575	0.830	-1.333	-1.828	2.652	0.480	0.074	0.073	0.212	0.040
	(0.857)	(1.325)	(1.223)	(8.892)	(25.672)	(32.778)	(0.707)	(0.237)	(0.198)	(0.185)	(0.175)

Notes: Figures in parentheses are standard errors. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 6
QARDL estimation results for South Africa.

Coefficients	Quantile levels										
	5th	10th	20th	30th	40th	50th	60th	70th	80th	90th	95th
Short-run related parameters											
φ_*	-0.422	-0.54	-0.567	-0.587	-0.28	-0.177	-0.055	-0.347	-0.464	-0.364	-0.652
	(0.372)	(0.316)	(0.236)	(0.214)	(0.223)	(0.242)	(0.238)	(0.224)	(0.219)	(0.282)	(0.318)
λ_*	-0.011	-0.001	0.01	0.001	-0.004	-0.004	-0.001	-0.006	-0.005	0.001	0.00007
	(0.054)	(0.006)	(0.049)	(0.006)	(0.037)	(0.035)	(0.006)	(0.08)	(0.07)	(0.02)	(0.006)
σ_*	-0.064	0.033	-0.03	-0.021	0.015	-0.043	-0.045	0.026	0.067	-0.031	-0.073
	(0.047)	(0.024)	(0.022)	(0.016)	(0.012)	(0.035)	(0.038)	(0.023)	(0.063)	(0.031)	(0.074)
π_*	0.107	0.061	0.072	0.064	-0.014	-0.014	0.008	-0.063	-0.047	-0.05	0.023
	(0.11)	(0.067)	(0.083)	(0.074)	(0.018)	(0.017)	(0.01)	(0.079)	(0.075)	(0.082)	(0.04)
ϕ_*	0.222***	0.209***	0.182***	0.194***	0.251***	0.201***	0.197**	0.262**	0.209**	0.108**	-0.033**
	(0.052)	(0.061)	(0.058)	(0.068)	(0.089)	(0.072)	(0.082)	(0.122)	(0.106)	(0.055)	(0.017)
ω_*	-0.092*	0.164*	0.201*	-0.081*	0.098*	-0.164	-0.026	0.089	-0.065	-0.069	-0.089
	(0.053)	(0.094)	(0.116)	(0.047)	(0.059)	(0.102)	(0.017)	(0.057)	(0.042)	(0.046)	(0.061)
θ_*	-0.022	-0.02	0.038	0.035	0.002	0.03	0.004	-0.002	0.002	-0.002	0.014
	(0.044)	(0.041)	(0.084)	(0.082)	(0.006)	(0.079)	(0.011)	(0.008)	(0.007)	(0.009)	(0.055)
Long-run related parameters											
ρ	-0.083**	-0.079**	-0.043	-0.039	-0.021	-0.041	-0.068**	-0.095***	-0.086***	-0.056**	-0.079**
	(0.04)	(0.036)	(0.027)	(0.025)	(0.024)	(0.026)	(0.028)	(0.027)	(0.027)	(0.028)	(0.034)
β_{WTI}	0.523	0.299	-0.292	-0.526	-0.697	-0.263	-0.253	-0.381	-0.152	0.243	0.183
	(0.433)	(0.371)	(0.499)	(0.572)	(1.167)	(0.492)	(0.304)	(0.252)	(0.288)	(0.496)	(0.347)
β_{GEPU}	-0.015	-0.405	-1.218	-1.758	-2.24	-1.13	-0.770*	-0.568*	-0.554	-0.213	-0.376
	(0.356)	(0.425)	(0.902)	(1.148)	(2.575)	(0.874)	(0.465)	(0.305)	(0.349)	(0.523)	(0.395)
β_{Gold}	0.786	0.471	1.234*	1.664*	2.066	1.161*	1.026**	1.352***	1.054**	0.549	0.514
	(0.531)	(0.479)	(0.681)	(0.855)	(1.848)	(0.689)	(0.446)	(0.378)	(0.482)	(0.845)	(0.591)
$\beta_{Sentiment}$	0.141*	0.044	0.054	0.087	0.039	-0.007	0.013	0.052	0.041	-0.018	0.009
	(0.081)	(0.05)	(0.073)	(0.102)	(0.187)	(0.099)	(0.06)	(0.042)	(0.052)	(0.095)	(0.064)
β_{FSI}	0.014	0.001	0.046	0.035	0.052	-0.015	-0.028	-0.034	-0.037	-0.031	-0.007
	(0.047)	(0.041)	(0.078)	(0.075)	(0.148)	(0.052)	(0.031)	(0.023)	(0.027)	(0.05)	(0.042)
β_{VIX}	-1.537**	-1.111**	-1.689*(1.009)	-1.786	-1.98	-0.797	-0.523*	-0.547***	-0.372*	-0.092	-0.47
	(0.665)	(0.46)		(1.11)	(2.202)	(0.606)	(0.294)	(0.194)	(0.216)	(0.401)	(0.297)

Notes: Figures in parentheses are standard errors. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

Table 7
Summary empirical results for the BRICS.

Variables	Type	Brazil					China					India					Russia					South Africa				
		EL	L	M	H	EH	EL	L	M	H	EH	EL	L	M	H	EH	EL	L	M	H	EH	EL	L	M	H	EH
Oil	short-run	NS	NS	NS	NS	NS	NS	NS	NS	NS	–	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	+	NS	NS	NS
	long-run	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Gold	short-run	+	+	+	+	+	+	+	+	NS	NS	+	+	+	NS	+	NS	+	NS	+	NS	+	+	+	+	+
	long-run	NS	NS	NS	NS	NS	+	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	+	NS	+	+	+	NS
VIX	short-run	NS	NS	NS	NS	NS	−	−	−	−	NS	−	−	−	−	−	−	−	−	−	NS	NS	NS	−	−	NS
	long-run	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	−	−	−	−	NS
EPU	short-run	NS	NS	NS	NS	−	NS	NS	NS	−	−	NS	NS	NS	NS	NS	−	NS	−	NS	NS	NS	NS	NS	NS	NS
	long-run	NS	NS	NS	NS	NS	+	NS	NS	NS	NS	−	NS	NS	NS	−	NS	NS	NS	−	−	NS	NS	−	−	NS
FSI	short-run	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	+	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
	long-run	NS	NS	NS	NS	NS	NS	−	−	NS	NS	NS	NS	−	−	−	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Sentiment	short-run	NS	NS	+	NS	NS	−	−	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	−	NS	NS	NS
	long-run	NS	NS	NS	NS	NS	+	+	NS	NS	NS	NS	NS	NS	−	−	NS	NS	NS	−	−	+	NS	NS	NS	NS

Notes: EL , L, M, H, and EH represent extremely low quantile (0.05 and 0.1 quantile) , low quantile (0.2 and 0.3 quantile), medium quantile (0.4, 0.5 and 0.6 quantile), high quantile (0.7 and 0.8 quantile) and extremely high quantile (0.9 and 0.95 quantile), respectively. NS means no significant relationships while + (−) indicates positive (negative) and statistically significant short-run or long-run relationships.

Table 8
Wald test for parameter constancy between quantiles.

Coefficients	Brazil	China	India	Russia	SA	Brazil	China	India	Russia	SA
	5th quantile against the 50th quantile					5th quantile against the 95th quantile				
Short-run related parameters										
$\varphi_* y$	0.0130	0.978	0.275	0.079	0.368	0.470	0.766	0.446	0.004	0.232
	(0.909)	(0.323)	(0.600)	(0.779)	(0.544)	(0.493)	(0.381)	(0.504)	(0.948)	(0.630)
λ_*	0.007	0.011	0.036	0.078	0.104	0.017	1.134	0.204	0.001	0.266
	(0.936)	(0.915)	(0.850)	(0.781)	(0.747)	(0.896)	(0.287)	(0.651)	(0.979)	(0.606)
σ_*	0.253	0.007	0.013	1.609	1.153	0.230	0.883	0.011	3.152*	1.143
	(0.615)	(0.933)	(0.909	(0.205)	(0.283)	(0.632)	(0.347)	(0.918)	(0.076)	(0.285)
π_*	0.059	0.026	0.221	0.993	0.016	0.008	3.936**	0.137	0.792	0.105
	(0.809)	(0.873)	(0.638)	(0.319)	(0.901)	(0.930)	(0.047)	(0.712)	(0.374)	(0.746)
ϕ_*	0.824	4.370**	0.035	0.226	0.215	0.614	3.434*	0.570	0.424	3.002*
	(0.364)	(0.037)	(0.852)	(0.634)	(0.643)	(0.433)	(0.064)	(0.450)	(0.515)	(0.083)
ω_*	0.023	1.651	1.021	0.166	0.021	0.037	0.625	2.814*	0.224	0.433
	(0.879)	(0.199)	(0.312)	(0.684)	(0.884)	(0.847)	(0.429)	(0.093)	(0.636)	(0.511)
θ_*	0.100	0.393	0.319	0.227	0.833	0.485	2.591*	0.088	1.101	2.305
	(0.752)	(0.531)	(0.572)	(0.634)	(0.361)	(0.486)	(0.100)	(0.767)	(0.294)	(0.129)
Long-run related parameters										
β_{WTI}	0.078	0.698	0.031	0.008	1.892	0.139	0.006	0.584	0.283	0.442
	(0.780)	(0.403)	(0.86)	(0.930)	(0.169)	(0.709)	(0.940	(0.445)	(0.595)	(0.506)
β_{GEPU}	0.070	1.332	0.672	0.007	1.480	0.036	0.005	0.125	0.071	0.450
	(0.792)	(0.249)	(0.412)	(0.935)	(0.224)	(0.850)	(0.942)	(0.72	(0.790)	(0.502)
β_{Gold}	0.119	0.21	0.067	0.008	0.228	0.266	0.005	0.105	0.041	0.115
	(0.731)	(0.647)	(0.795)	(0.929)	(0.633)	(0.606)	(0.944)	(0.746)	(0.839)	(0.734)
$\beta_{Sentiment}$	0.163	0.121	0.691	0.012	1.510	0.208	0.005	0.575	0.575	1.736
	(0.686)	(0.728)	(0.406)	(0.911)	(0.219)	(0.648)	(0.942)	(0.448)	(0.448)	(0.188)
β_{FSI}	0.036	0.419	0.21	0.006	0.201	0.178	0.001	0.082	0.020	0.118
	(0.849)	(0.517)	(0.647)	(0.937)	(0.654)	(0.673)	(0.972)	(0.774)	(0.889)	(0.731)
β_{VIX}	0.015	0.004	0.747	0.007	0.768	0.021	0.006	2.840*	0.003	2.025
	(0.903)	(0.949)	(0.387)	(0.934)	(0.381)	(0.884)	(0.941)	(0.092)	(0.955)	(0.155)

Notes: Figures in parentheses are p values. ***, ** and * denote statistical significance at 1%, 5% and 10% level respectively.

results also show that β_{GEPU} is significantly positive for China at extremely low quantiles, denoting an upward trend of long-run co-movement between EPU and Chinese stock markets; One possible explanation is that consumers and companies might hoard inventory ahead of time because of concern about shortages in periods of high policy uncertainty, and this raises the price of commodities as well as corporate profits and stock prices. But the other BRICS countries (i.e., India, Russia, and South Africa) have a downward trend of long-run co-movement between EPU and stock markets. Previous empirical studies confirm the significant negative effect of uncertainty shocks on macroeconomic activities and stock markets. When the macroeconomic environment is more uncertain, it becomes more difficult to evaluate the asset price generation process and make accurate investment decisions (Chang et al., 2015). The negative effects of EPU on stock prices emerge through the following channels. First, EPU could make firms, individual investors, and other economic actors change or delay critical decisions (Gulen and Ion, 2015). Second, EPU might increase financing and production costs by influencing supply and demand channels, reducing investment, and depressing the economy. On the demand side, investors might delay their purchasing and investment plans when uncertainty in taxes, interest rates, and regulation is high. On the supply side, when economic policy is uncertain over a long period, commodity producers will be likely to reduce production. Third, EPU might raise risk in financial markets, resulting in less government protection of markets (Pastor and Veronesi, 2012). More important, stock markets react differently to EPU shocks, depending on their conditions (i.e., bearish, normal, or bullish).

An insignificant correlation is observed between financial stress and the Brazilian, Russian, and South African stock markets in both the short and long run, as ω_* and β_{FSI} are insignificant across quantiles for these countries. In China, current and prior changes in financial stress have no impact on stock markets in the short term, but financial stress has a negative effect on stock markets at the 30th and 40th quantiles in the long run. Furthermore, financial stress has a positive impact on the Indian stock market at extremely high quantiles in the short run, but it has a downward trend in the long-run relationship with the Indian stock market from the 40th to the 95th quantiles. This finding is consistent with the behavior of investors. That is, as financial stress rises, holding assets in the global market becomes riskier, and this information might spread quickly to other stock markets. Under these market conditions, investors then require a premium to hold shares, and hence stock prices drop. Economic theory also holds that greater financial stress changes investment and consumption plans. Their correlation via the investment channel is mainly influenced by long-term interest rates and the cost of capital, whereas the correlation via the consumption channel is primarily affected by wealth and income. Therefore, financial stress might affect the allocation of assets by international investors. For instance, when financial stress is high, which indicates that the global financial market is unstable, risk might drive international investors to turn to safer choices in allocating their portfolios or switch to other countries that they consider less affected by financial stress.

The short-run effects of investor sentiment on the Indian and Russian stock markets are insignificant, the short-run effects of investor sentiment on the Chinese and South African stock markets are significantly negative at lower quantiles, but significantly positive only at medium quantiles for the Brazilian market. In terms of the long-run relationship, investor sentiment has a significantly positive effect on the Chinese and South African stock markets at low quantiles, but a significantly negative impact on the Indian and Russian stock markets at high quantiles. Baker and Wurgler (2006) argue that the impact of investor sentiment on all stocks is inconsistent, and investor sentiment is more inclined to influence certain classes of stocks, especially those that are difficult to value or arbitrage. They show that when investor sentiment is high/low, these stocks are subjected to over/under pricing and then rebound.

Table 7 summarizes the empirical results described in Sections 4.1 to 4.3. Overall, BRICS stock markets do not react to global factors in a uniform way, but the sign of the impact of global factors on BRICS countries is largely consistent. The effects of gold prices and the VIX on BRICS stock markets are more significant in the long run than in the short run. A decline in the VIX is associated with an increase in stock prices, whereas gold prices show positive co-movement with stock prices. EPU, the FSI, and investor sentiment play an important role in the short term, with predominantly negative correlations. The empirical results also demonstrate that the estimated coefficients are heterogeneous across quantiles and across countries. The differential impact of global factors on the stock markets of BRICS countries might be related to the heterogeneity of their financial markets and the nonsynchronous nature of their financial reforms. The stock markets in each country might be at different stages of development, so their sensitivity to changes in global factors, such as economic policies, affects stock market prices differently.

4.4. Asymmetric and time-varying patterns between major global factors and BRICS stock markets

In this section, the Wald test is used as an inter-quantile test to examine the persistence of the short- and long-run parameters at different quantile levels (Table 8). The statistical differences across quantiles are confirmed by the rejection of the null hypothesis of the equality test. Similarly, the Wald test examines the nonlinearity of the short- and long-run parameters to assess locational asymmetry (Cho et al., 2015). In general, the Wald tests fail to reject the null hypothesis for ρ and the long-run cointegrating parameters (β_{WTI}, β_{GEPU}, β_{Gold}, $\beta_{Sentiment}$, β_{FSI} and β_{VIX}) for all BRICS countries but rejects the null hypothesis for β_{VIX} in India. These results mean that the estimated parameters are statistically significant for some quantiles and differ across quantiles. However, this difference is not significant, indicating that major global factors maintain almost constant dependence with BRICS stock markets in the long run. The results on the cumulative short-run effects of investor sentiment on BRICS stock markets demonstrate that the Wald test rejects the null hypothesis of equality across quantiles for China and South Africa but fails to reject it for India, Brazil, and Russia. The Wald test also rejects the null hypothesis of cumulative short-run effects of gold prices on the BRICS stock markets only in China, but fails to reject the null hypothesis for Brazil, India, Russia, and South Africa. Also, the cumulative short-run impact of EPU, the VIX, and financial stress on BRICS stock markets is asymmetric only in Russia, China, and India, respectively, and the remaining two BRICS countries fail to reject the null hypothesis. Finally, oil prices and global stock market volatility have a symmetric impact on all

BRICS stock markets in the short run. Although BRICS countries are typical representatives of emerging economies, some differences are found in the performance of the coefficient estimates across quantiles. The differences are likely to be related to diversity in national statistics in the five countries, such as trade openness, the ratio of stock market capitalization to the gross domestic product, and the net trading position of the country. Indeed, portfolio outcomes could be improved by including asymmetric characteristics and analyzing their short- and long-run effects.

Because the sample period is quite long, it is critical to consider time-varying mechanisms between the major global factors and BRICS stock markets. Models that span a long period and exclude the structure of time-varying patterns might produce an average trend in the relationships that can only be tested by employing a series of regime-switching models. For this study, a robust rolling-window approach is applied to test the wide possible range of scenarios. This study selects a window with a length of 150 months, which could meet the requirements of the QARDL approach within expectation. Appendix Figs. A1-A5 display the rolling-quantile estimation of the six short-run coefficients (λ_*, π_*, θ_*, σ_*, ω_*, and ϕ_*), with 95% confidence intervals for BRICS countries.[7] On the whole, the rolling-quantile estimates of all short-run coefficients (λ_*, π_*, θ_*, σ_*, ω_*, and ϕ_*) show strong time-varying patterns. Specifically, Appendix Figs. A1-A5 show the time-varying linkage between global factors and the BRICS stock markets. The time-varying patterns distinguish the subperiods with strong correlations and the periods with negative and positive correlations. A reasonable explanation of the time-varying patterns is that the potential linkage among variables might change over time because the shocks at each point in time are heterogeneous. Policy makers should not ignore the time-varying relationships between global factors and BRICS stock markets when implementing economic and financial policies. Timely decisions can be useful in reducing the destabilizing impact of shocks on stock markets and global factors.

5. Conclusions and policy recommendations

This paper studies the short- and long-run relationship between a broad series of global factors and BRICS stock markets by applying the QARDL model. One of the advantages of this model is that it enables us to study the short- and long-run nexus under different market conditions. Furthermore, Wald tests and the rolling-estimation technique are used to explore the asymmetric and time-varying linkage between global factors and BRICS stock markets. Our empirical results show that the effects of gold prices and the VIX on BRICS stock markets are more significant in the long run than in the short run. A decrease in the VIX is associated with higher stock prices, whereas gold prices have positive comovements with stock markets. The irrational factors, such as EPU, the FSI, and investor sentiment, play a critical role in the short term, and negative interdependence is dominant.

The estimation results for the BRICS countries are heterogeneous, depending on the countries' characteristics, and have quantile-varying properties. In terms of the effects of commodity markets, oil prices have insignificantly symmetric dependence with BRICS stock prices in the short and long run. Gold prices fluctuate with BRICS stock prices in both the short and long run (except Brazil and India in the long run), but the dependence pattern is asymmetric only for China in the short run. The effects of global stock market volatility have a significantly negative and symmetric relationship with BRICS stock markets in the short and long run (but the long-run relationship with South Africa is significant). In general, these three rational factors play a dominant role in BRICS stock markets in the short run. Moreover, EPU has a negatively symmetric effect on BRICS stock markets in the short and long run (but a positive impact on China in a bear market). Financial stress is a negatively relevant factor only for China and India in the long run but has positive co-movement for India in a bull market. The short-run effects of investor sentiment on Chinese and South African stock prices are significantly negative in a bear market, but in the Brazilian market they are significantly positive only under normal market conditions. In terms of long-run relationship, investor sentiment exhibits a significantly positive lower-tail dependence with the Chinese and South African stock markets, but negative higher-tail dependence with the Indian and Russian stock markets.

Our findings lead to several policy implications. First, because of the financialization of the commodity markets, oil and gold can offer protection against losses and hedge risk when traditional assets are in sharp decline. Second, the behavior of the BRICS stock markets is related to global economic policy, thus investors and other stock market participants should be more aware of the impact of their decisions and behaviors on stock markets under various market conditions (i.e., bearish, normal, and bullish). Moreover, when formulating policies, the government needs to consider the sustainability and stability of the policies. Frequent policy changes can lead to changes in investors' psychological expectations and irrational behavior, which in turn can lead to market overreaction and is not conducive to stable development of the stock market and financial market stability. Third, financial stress can also affect how international investors allocate their assets. When global financial market is unstable, higher risk can drive international investors to turn to safer choices by reallocating their portfolios or shifting to other countries that they believe are less affected by financial stress. It is essential to take relevant measures to boost the confidence of international investors in equity markets, which can safeguard their benefits against uncertainties and risks originating from the global markets. Notably, because the short- and long-run effects of these global factors on BRICS stock markets vary, it is vital for investors to accurately forecast stock market behavior by distinguishing the frequency nexus between major global factors and stock prices.

Although the subject of this paper is the BRICS countries, the rationale argued regarding differences in information openings in the markets can be extended to other developed markets. Further research could compare our results on the BRICS stock markets to those on mature markets or examine co-movements between irrational global factors and developed stock markets. Additionally, future work could allow for two or more breaks by performing tests. Such a methodological innovation would enable further insights

[7] To save space, the results of the rolling estimates of the long-run coefficients (β_{WTI}, β_{Gold}, β_{VIX}, β_{GEPU}, β_{FSI}, and $\beta_{Sentiment}$) are not reported, and the results are available from the corresponding author upon request.

to be drawn about the importance of structural changes in stock prices.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ecosys.2022.101015.

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