Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 2462077, 19 pages
https://doi.org/10.1155/2022/2462077

Research Article

Quantifying Information Flows among Developed and Emerging Equity Markets

Ebenezer Boateng,[1] **Peterson Owusu Junior**,[1] **Anokye M. Adam**,[1] **Mac Jr. Abeka**,[1] **Thobekile Qabhobho**,[2] **and Emmanuel Asafo-Adjei**[1]

[1]*Department of Finance, School of Business, University of Cape Coast, Cape Coast, Ghana*
[2]*Department of Economics, Faculty of Business and Economic Sciences, Nelson Mandela University, Port Elizabeth, South Africa*

Correspondence should be addressed to Emmanuel Asafo-Adjei; eaadjei12998@gmail.com

Received 5 June 2022; Accepted 14 July 2022; Published 22 August 2022

Academic Editor: Yuxing Li

We rely on daily changes in implied volatility indices for the US stock market (VIX), developed markets excluding the US (VXEFA), stock markets in Brazil (VXEWZ), Russia (RVI), India (NIFVIX), China (VXFXI), and the overall emerging market volatility index (VXEEM) to examine the degree of information flows among the markets in the coronavirus pandemic. The study also employs the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to decompose the data into intrinsic mode functions (IMFs). Subsequently, we cluster the IMFs based on their level of frequencies into short-, medium-, and long-term horizons. The analysis draws on the concept of Rényi transfer entropy (RTE) to enable an assessment of linear as well as non-linear and tail-dependence in the markets. The study reports significant information flows from BRIC volatility indices to the overall emerging market volatility index in the short-and medium-terms and vice versa. We also document a mixture of bi-directional and uni-directional flow of high risk information and low risk information emanating from emerging equity markets and from the developed markets. We find that the transmission of high risk information is largely dominated by the developed markets (VIX and VXEFA). In the midst of high degree of contagion, our findings reveal that investors can find minimal benefits by shielding against adverse shocks from the developed markets with a combination of stocks from India and other equities in the emerging markets in the short-term, within 1–15 days. For as low as 1–5 days, the empirical evidence indicates that a portfolio consisting of stocks from Russia and Brazil also offer immunity to shocks from the VXEFA. Our study makes an important empirical contribution to the study of market integration and contagion among emerging markets and developed markets in crisis periods.

1. Introduction

The integration of global economies due to cross-border trade and investment flows has increased tremendously over the past three decades. While this phenomenon has had positive repercussions on global stock market development and financial stability [1–4], it has also increased considerably the correlations among global equity markets. Corollary to this, the diversification benefits that were apparent among markets have diminished significantly [5]. This phenomenon has also heightened the search for segmented markets by international investors. In this regard, the degree of integration of emerging equities with developed markets has become topical amongst finance scholars in recent times [6–8].

Although emerging equities' correlations with developed equities have increased over the years, some authors still argue that stocks from emerging markets should be considered as segmented [9, 10]. In support of the segmentation of emerging stock markets, Akbari et al. [11] reveal that while economic integration has been achieved with global markets, financial integration has been slow. Bekaert and Harvey [12] are also of the view that emerging market equities are still not fully integrated with developed markets. To a certain degree, this explains the reason for the present disparities in the percentage market capitalization of emerging equity markets in the investable world equity benchmark as compared to the number of emerging economies in the world. While almost 80% of countries have been classified to be emerging and account for about 59% of total global GDP [13], these economies surprisingly account for just around 13% of global equity capitalization. According to Bekaert and Harvey [12], the less developed nature of their financial markets in contrast to that of developed countries' features makes emerging markets equity worth considering in portfolio and asset allocation decisions of international investors.

Aside from the aforementioned characteristics, several other factors make stocks from emerging markets appealing for portfolio construction and asset allocation to international investors. Portfolios that include stocks from emerging markets remain economically beneficial to investors. This is because the equities have historically produced high risk-adjusted returns [14, 15] with an enhanced investment opportunity set [16, 17]. In addition, the economic outlook of emerging economies has been welcomed with such optimism as never anticipated. These economies are today the primary drivers of growth and wealth accumulation in the world. They also house a lion's share of the world's population and are home to the world's largest reservoir of future consumers [13]. Moreover, the contribution of country-specific factors to the variance in equity returns is also twice as much as industry-specific factors in each emerging market, making equity price volatilities vary for each emerging market [18, 19]. Corollary to this, Lyócsa and Baumöhl [20] posited that during turbulent times, emerging markets exhibit lower risk-return correlations compared to developed markets.

Despite the enormous potential attributed to emerging markets, they possess enormous risks for investors. With relatively lower levels of financial development and weaker institutional structures, emerging economies are imbued with high levels of information asymmetries [21] and lower investor protection [22]. These result in high cost of enforcing contracts. More likely than not, the speed to achieving full financial integration into global equity markets is being hampered by the lower level of financial development and high level of investment risk that is blatant in emerging economies [11]. Nonetheless, this phenomenon is not pervasive across all emerging economies. Stressing these similar characteristics of emerging markets, however, should not obscure the fact that they are not homogenous. Emerging countries differ from each other in terms of political systems, legal structures, regional heterogeneity, and the speed of institutional and economic reforms [23].

Beginning from the early 1980s, most of the emerging economies including BRIC countries have undertaken several economic and financial reforms due to economic integration and enhanced financial liberalisation. These economies adopted electronic trading systems, improved the strength of investor protection, enhanced the enforcement of anti-insider trading laws, strengthened connections between domestic exchanges, and enhanced significantly their regulatory and disclosure requirements [24, 25]. These have made such economies, particularly BRIC more attractive for USA and other international investors. Predictably, these investors seek optimal portfolio allocation, international diversification, and hedging strategies [24, 26]. Notwithstanding, the extent to which such benefits exist is consequent on the level of stock market integration.

Intuitively, emerging markets should be heavily linked to the USA market and equities from other developed markets due to underlying trade and investments. Therefore, shocks from these developed markets should be transmitted to the emerging markets as it affects exports and investments made by multinational companies from countries in the developed markets. This form of interdependences allows shocks, whether of local or global nature to be transmitted across the countries due to real and financial linkages [27]. In particular, Bhattarai et al. [28] note that uncertainty shocks from the US exhibit significant uncertainty spillovers to emerging economies. Horvath and Zhong [29] had also documented that these shocks have sizeable impacts on macroeconomic fluctuations in emerging countries and that a considerable fraction of these impacts is through the domestic stock market. While this does not normally constitute contagion in normal conditions, their occurrence during turbulent conditions coupled with their adverse effects can be expressed as contagion [30–33]. Contagion can also be seen from the comovements of financial markets as a result of "irrational" phenomena, such as financial panics, herd behavior, loss of confidence, and increased risk aversion in times of crisis [30]. Hence, it is explicated to investigate contagion in light of common occurrence in countries with similar economic scenarios from regional blocs (Monsoonal effects), shared economic fundamentals arousing high linkages, and triggering of crisis elsewhere from another country for reasons inexplicable by macroeconomic indicators [34, 35] driving global economic shock.

In this paper, we examine the information flows among developed markets and emerging markets. We do not employ price or return series because the dynamics of contagion and integration are captured faster and clearer through volatility indices than stock indices [36]. Moreover, we take a slightly different perspective from studies that examine integration with realized volatility [12] by employing implied volatility indices. This is because volatility series obtained from stock indices are historical and may not accurately capture future uncertainties [37]. The implied volatilities however, provide an accurate measure of uncertainty as it captures historical information of stock prices and investor sentiments about future expectations of stock price movements in tandem [5, 8, 38]. Since volatility indices are also traded securities, they are useful for portfolio optimization and asset allocation decisions. Due to the superiority of the information content of the implied volatilities which has been well acknowledged and documented in the literature [36, 39, 40], we rely on forward-looking indices, the VIX, VXEFA, VXEWZ, RVI, NIFVIX, VXFXI, and VXEEM which depicts implied volatility indices from the US stock market, developed markets (excluding the

USA), Brazil, Russia, India, China, and overall emerging market index respectively.

We note that employing changes in volatility indices rather than stock returns presents significant challenges due to variations that are more intense in the former than the latter. Volatility indices reflect asymmetric, non-normal, and time-varying behaviors of investors [8]. Such behaviors may present issues of non-linearities, and non-stationarities [32, 41]. Noise, which is a regular phenomenon in stock market data, can be more germane to volatility indices. We deal with the inherent complexities in the dataset by employing the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to decompose the series into intrinsic decomposition (IMF). This represents different time horizons and in consequence, smoothens out the underlying complexities. Particularly, the CEEMDAN removes noise from the dataset which may be as a result of irrational investor behaviours. Subsequently, we utilise the Rényi entropy to assess the information flows among the developed equity volatility indices and the emerging market indices. As a unique variant of the transfer entropy techniques, Rényi entropy differentiates between tails of the distribution by assigning weights. Unlike the Shannon entropy, Rényi entropy allows emphasis on different distribution areas, depending on the weighting parameter. We surmise from the characteristics of financial time series data and the studies of [5, 8] that volatility indices are tail-distributed. These fat tails can be more apparent in the pandemic.

We contribute to the following First, it has been shown that noise in time series can be more pronounced than the signal's effect, thereby affecting the results to the some extent [32, 39, 41]. In our attempt to circumvent this, the study becomes the first to employ noise-assisted technique -CEEMDAN- on equity markets in empirical discussions on the linkages between emerging and developed equity markets. The CEEMDAN decomposition also enables investors to tailor their trading strategies taking into consideration the heterogeneous and adaptive nature of their portfolio requirements and market opportunities. Second, the application of the Rényi transfer entropy provide a non-parametric, non-linear, and asymmetric lens to the discussions on market contagion and integration in crisis periods.

While this approach helps to overcome a number of inherent complexities in financial time series data, the output also delineates higher-risks assets from lower-risk assets. In the midst of the pandemic which may quicken financial contagion, such classification enables investors to pair higher-risk equities with lower-risk equities in their portfolios to minimize risks. Instead of spillovers, we classify the extent of significant high risk information in the pandemic among equity markets to measure the degree of contagion in this study. This offers a new lens to the extant literature on financial market contagion and integration. In this instance, portfolio diversification strategies may not work in equity markets that receive significant high risk information. Similar to this perspective, Gallegati [42] noted that contagion makes correlations among markets break down in times of crisis, diminishing any benefits from diversification.

Overall, the empirical evidence from the Rényi entropy reveals both bi-directional and uni-directional flow of high risk information and low risk information emanating from emerging equity markets and from the developed markets. We find that the flow of high risk information is largely dominated by the developed markets (VIX and VXEFA). The study also document significant information flows from BRIC volatility indices to the overall emerging market volatility index in the short- and medium-terms. In the light of the flight to safety triggered by the coronavirus pandemic, our findings has important implication for investment decisions. The next section of the study presents the methodology employed in the study. We then proceed with the analysis of the results and its discussion. Finally, the conclusion and implications are discussed.

2. Literature Review

The possibility of examining the dynamics of time series in frequency domains should be more appealing to finance scholars because investor behaviour tends to differ across time [32, 43, 44]. We draw theoretical insights from the adaptive market hypothesis (AMH), heterogeneous market hypothesis (HMH) and competitive market hypothesis (CMH) in the regard. Lo [45, 46] asserts in the AMH that markets evolve according to varying degrees of efficiency. Adaption, innovation, competition, and mutation result in a decrease and increase in the intensity of market efficiency due to varying market conditions [47, 48]. The implication of the AMH for investors is that opportunities for profits evolve, which should affect the timing of implementing strategies, justifying the importance of active portfolio management. Müller et al. [49] also contend in the HMH that investors analyze events and news and employ trading strategies taking into consideration their different time horizons. This, we define as intrinsic time. Consequently, the efficiency of markets and the level of investor risk aversion could differ in the COVID-19 pandemic.

Though the emergence of the recent COVID-19 turmoil has affected countries differently due to differences in responses and other factors, the shocks to international trade and transnational flow of funds may open the floodgates for financial contagion and financial harm. The damage to most markets can be quite extensive due to weak precautionary measures and poor response rates [31]. This appears to have caused a fragility in the global financial system and public health care delivery. Seen as a country-specific phenomenon as of the early January in 2020, the degree of contagion and pace of transmission has rendered almost all economies crisis-ridden.

Moreover, measures that have been employed to minimize the spread has also curtailed economic activity significantly. These have triggered movements of funds to safer economies, known as the flight to safety [31]. In the light of increased vagueness in economic forecasts as well as heightened uncertainty in asset prices due to the pandemic, a typical feature of investors is their changing risk appetites that causes a recalibration of portfolios to match their updated competing risk and reward preferences [32]. This, together with fear also causes investors to switch among different markets. With the inceasing levels of financial openness and international trade around the globe, developed but also emerging markets have become closely interrelated to arouse contagion during crisis periods.

On the empirical front, this study is closely knit to the studies of [5, 8]. The latter examined the cross-market volatility linkages among the VIX, the developed market index (VXEFA), and the VXEEM. Their findings divulged that the VIX has information content that is stronger for the VXEEM than the VXEFA, implying a stronger degree of correlation between emerging markets and VIX than other developed markets. The former also assessed the relationships between changes in the implied volatility for US stock market (VIX) and changes in the Brazilian (VXEWZ), Chinese (VXFXI), and overall emerging market volatility (VXEEM) indices. They employed the mixed Quantile regression-Copula methodological approach and documented a strong positive and asymmetric linkages between VIX and the volatilities of the emerging market indices.

Unlike the aforementioned studies, we examine the information flows between BRIC volatility indices and the overall emerging market volatility index (VXEEM). Lyócsa and Baumöhl [20] proffer that in turbulent times, emerging markets exhibit lower risk-return correlations. In consequence, the economies of BRIC countries can offer diversification potentials for international investors in the pandemic. In this vein, the paper investigates whether the overall emerging market index has the complete information contents of the BRIC markets, thereby eroding all diversification benefits between them. To our knowledge, this is the first empirical attempt to examine volatility linkages among the emerging market index and the BRIC indices. Second, we quantify the flow of information between the developed equity markets and the emerging markets to assess the nature of causality during the pandemic. Although the linkages between developed and emerging equity markets were the focus of the studies of [5, 8], our study differs in terms of the sample window and data treatment. The present discussion is conducted with a data coverage in the period of the COVID-19 pandemic–an era with the greatest uncertainty in financial markets and economic activity. Gallegati [42] avers that portfolio diversification strategies may not work in turbulent times as the correlation among markets could break down. Thus, the COVID-19 sample window provide a uniquely rich dataset to examine the dynamics of contagion and market integration. More importantly, our empirical study is conducted in frequency domains.

3. Methodology

This section discusses the use of CEEMDAN and the Rényi transfer entropy (RTE) in the empirical study.

3.1. CEEMDAN. The use of empirical mode decomposition (EMD) techniques to decompose time series data that have received enormous attention over the years from researchers due to its purely data-driven algorithm to separate scales which are exclusive of predefined basis functions, compared to wavelet analysis [41, 50, 51]. For instance, in the wavelet decomposition, a mother wavelet is required to decompose a signal which is subjective in its selection and highly influential [50]. However, the EMD method resorts to scale mixing problem. This was addressed with the ensemble empirical mode decomposition method (EEMD). Wu and Huang [52] incorporated a randomly generated white noise series to the original signal in their EEMD. Further, Torres et al. [53] developed the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to solve the residual noise in the reconstructed signals within the EEMD. The CEEMDAN is superior to the EMD, EEMD and CEEMD [32, 41]. Further, it solves the problem of low decomposition efficiency, and saves a great deal of processing power. Again, the output of CEEMDAN follows a Gaussian distribution, so that each IMF follows N (θi, 1) [54]. This is important because the observed data often describe a set of phenomena which may be of different kinds, i.e. which may include a phenomena of different quality [55], which presents themselves in quantitative discrepancies in financial time series.

We decomposed the volatility indices into seven IMFs and a residual using the libeemd *R* package developed by Helske and Luukko [56]. The application of the algorithm follows the following procedures:

Start the number of realizations N, noise parameters, index for IMF $j = 1$.

Perform the EMD for N realizations; $Sm(t) = S(t) + \delta_o Wn(t)$, $i = 1, 2, 3, \ldots, N$, where n denotes to the index for realizations; $Wn(t)$ is the white noise series added to the candidate signal, and δ_o is the noise parameter for the initial step.

The ensemble mean intrinsic mode functions (IMF) are estimated as:

$$\overline{\mathrm{IMF}_n(t)} = \frac{1}{N}\sum_{n=1}^{N} \mathrm{IMF}_n(t). \tag{1}$$

The exclusive first residue can be calculated as:

$$r_1(t) = s(t) - \overline{\mathrm{IMF}_n(t)}. \tag{2}$$

Evolve N number of realizations, then the operator $E_j(\cdot)$ produces J^{th} the mode obtained by EMD.

$$\begin{gathered} r_{jn}(t) = r_j(t) + \delta_j E_j(Wn(t)), \\ n = 1, 2, 3, \ldots, N, \\ \overline{\mathrm{IMF}_{j+1}(t)} = \frac{1}{N}\sum_{n=1}^{N} E_1\left[r_{jn}\right]. \end{gathered} \tag{3}$$

The final step is to calculate the j^{th} residue, where $j = j + 1$:

$$r_j(t) = r_{j-1}(t) - \overline{\mathrm{IMF}_j(t)}. \tag{4}$$

3.2. Rényi Transfer Entropy. As a precursor to our discussion on the RTE, we start with the concept of Shannon entropy introduced by Shannon [57] as a measure of uncertainty upon which transfer entropy is embedded in information theory. We consider a probability distribution with diverse results of a given experiment, p_j. In accordance with Hartley [58], each symbol's average can be written as:

$$H = \sum_{j=1}^{n} P_j \log_2\left(\frac{1}{P_j}\right) \text{bits}, \tag{5}$$

where n represents the number of distinct symbols with respect to the probabilities P_j.

The Shannon entropy posits that for a discrete random variable (J) with probability distribution $(P(j))$, the average number of bits needed to optimally encode independent draws [59] is given as:

$$H_J = -\sum_{j=1}^{n} P(j)\log_2 P(j). \tag{6}$$

With the notion of Markov processes, Shannon entropy is aligned with the concept of information efficiency espoused by Kullback and Leibler [60] to measure the flow of information in the two time series. We present I and J as two discrete random variables with corresponding marginal probabilities of $P(i)$ and $P(j)$, joint probability $P(i, j)$, with dynamic structures in line with a stationary Markov process of order k (Process I) and I (process J). The Markov property implies that the probability to observe I at time $t+1$ in state i conditional on the k previous observations is $p(i_{t+1}|i_t,\ldots,i_{t-k+1}) = p(i_{t+1}|i_t,\ldots,i_{t-k})$. To encode the observation in $t+1$, the average bits number required once the ex-ante k values are known, can be illustrated as

$$h_j(k) = -\sum_i P\left(i_{t+1}, i_t^{(k)}\right)\log P\left(i_{t+1}|i_t^{(k)}\right). \tag{7}$$

where $i_t^{(k)} = (i_t,\ldots,i_{t-k+1})$ (analogously for process J). In a two-way perspective and in accordance with the Kullback-Leibler distance, quantification of the deviations from the generalized Markov property from process J to process I is made $P(i_{t+1}|i_t^{(k)}) = P(i_{t+1}|i_t^{(k)}, j_t^{(I)})$.

The Shannon transfer entropy can thus be presented as:

$$T_{J\longrightarrow I}(k,l) = \sum P\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)\log\frac{P\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}{P\left(i_{t+1}|i_t^{(k)}\right)}. \tag{8}$$

where $T_{J\longrightarrow I}$ estimates the flow of information from J to I. In a similar vein, $T_{I\longrightarrow J}$, which measures information flow from I to J, can also be obtained. The net information flows can be estimated by differencing, i.e. taking the difference between $T_{J\longrightarrow I}$ and $T_{I\longrightarrow J}$.

Having discussed the Shannon entropy, we proceed with Rényi's variant of transfer entropy. This variant is based on a on a weighting parameter q [61] and can be calculated as:

$$H_J^q = \frac{1}{1-q}\log\sum_j P^q(j), \tag{9}$$

with $q>0$. For $q \longrightarrow 1$, Rényi entropy converges to Shannon entropy. For $0<q<1$ means that a low probability event receives greater weight, while for $q>1$ the weights benefit outcomes j with a higher initial probability. In consequence, Rényi entropy allows emphasis on different distribution areas, depending on the weighting parameter q [32, 59, 62] relative to the Shannon entropy.

On the application of the escort distribution [63] $\varnothing_q(j) = p^q(j)/\sum_j p^q(j)$ with $q>0$ to normalize the weighted distributions, we derive Rényi's transfer entropy as;

$$\mathrm{RE}_{J\longrightarrow I}(k,l) = \frac{1}{1-q}P\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right) \log\frac{\sum_i \varnothing_q\left(i_t^{(k)}\right)P^q\left(i_{t+1}|i_t^{(k)}\right)}{\sum_{i,j}\varnothing_q\left(i_t^{(k)}, j_t^{(I)}\right)P^q\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}. \tag{10}$$

It is worth noting that the calculation of the Rényi transfer entropy can result in negative values. In such a situation, knowing the history of J depicts even greater uncertainty than would otherwise be indicated by only knowing the history of I alone [32, 44].

Marschinski and Kantz [64]note that the transfer entropy estimates are efficient in large samples but produce bias results in small results. The correction of this bias is possible with a shuffled version given below:

$$\mathrm{ETE}_{J\longrightarrow I}(k,l) = T_{J\longrightarrow I}(k,l) - T_{J\text{shuffled}\longrightarrow I}(k,l), \tag{11}$$

where $T_{J\text{shuffled}\longrightarrow I}(k,l)$ is the transfer entropy using a shuffled version of the time series J. This is achieved through a random realignment of values drawn from the observed time series J to generate a new time series. The resultant series causes a destruction of the time series of J, taking into consideration the statistical dependencies between J and I. This commands a zero convergence of $T_{J\text{shuffled}\longrightarrow I}(k,l)$ when the sample size is increasing. This presupposes that any nonzero value of $T_{J\text{shuffled}\longrightarrow I}(k,l)$ is attributable to small sample effects. In consequence, the replication of the shuffling, together with the average of the resulting estimates across all replications becomes the estimator for the bias due to the small sample which are subtracted from the Rényi transfer entropy estimates which helps to derive effective transfer estimates that are unbiased.

Relying on a Markov block bootstrap, the statistical significance of the transfer entropy estimates, as given by (11) can be examined as indicated by Dimpfl and Peter [65]. This preserves the dependencies within the variables J and I, but eliminates the statistical dependencies between J and I contrary to shuffling. Repeated estimation of transfer entropy then provides the distribution of the estimates under the null hypothesis of no information flow. The associated p − value is given by $1-\widehat{q}T$, where $\widehat{q}T$ denotes the quantile of the simulated distribution that is determined by the respective transfer entropy estimate [59].

Finally, algorithms of the transfer entropy are based on discrete data. This requires a discretization of the continuous data employed in the study. To address this, symbolic encoding is performed which partitions the data into finite set of bins [32, 59]. For a given number of bins n, with bounds $q_1, q_2, q_3, q_4 \ldots, q_{n-1}$ $(q_1 < q_2 < q_3 < q_4 \cdots < q_{n-1})$ and a continuous observed time series data y_t, its partitioning is given by:

$$s_t = \begin{cases} 1, & y_t \le q_1, \\ 2, & q_1 < y_t < q_2, \\ \vdots & \\ n-1, & q_{n-2} < y_t < q_{n-1}, \\ n, & y_t \ge q_{n-1}. \end{cases} \quad (12)$$

The size and distribution of the observed time series informs the selection of the number of bins. In empirical studies that place importance on tail observations, binning is usually based on left tail and right tail quantiles [32]. The selection of the 5% and 95% empirical quantiles to represent lower and upper bounds of the bin respectively makes the task easier. This gives rise to three symbolic encodings comprising the lower tail with negative volatility shocks (5%), the upper tails with positive shocks (95%) and the normal shocks which is in the second bin (middle 90%).

3.3. Data and Preliminary Analysis. The study employs daily changes in the volatility indices from January 6, 2020 to September 23, 2021 obtained from investing.com to examine the information flows among the VIX, VXEFA, VXEWZ, RVI, NIFVIX, VXFXI, and VXEEM which depicts implied volatility indices from the US stock market, developed markets (excluding the USA), Brazil, Russia, India, China, and overall emerging market index, respectively. We begin the preliminary analysis with plots of the series and the volatility changes. This is followed by a descriptive analysis of the volatility changes and the decomposed data.

Figure 1 illustrates the plot of the volatility indices and the ln-changes changes in the indices. It is observed that the beginning of the COVID-19 pandemic saw a massive rise in investor fear in both developed equities and emerging markets. This behavior at the start of the pandemic is shown by all indices. We attribute this to both country-specific factors and volatility spill overs arising from panic and fear at the start of the pandemic in the first quarter of 2020 which resulted in increased investor risk aversion. Gunay [31] notes that the vague picture of economic stability painted as well as unstable asset prices at the beginning of the pandemic resulted in massive recalibrations of investors' portfolios in accordance with their new level of risk aversion. In these periods, stock markets took the biggest hits [31]. Thus, it is not startling that investor fear was skyrocketing in record-breaking highs. On the right-hand-hand side is the plot of the changes in the indices. The volatility clustering exhibited is a regular feature of financial time series data.

From Table 1, the mean changes in the volatility indices are quite low, approaching zero. This is because volatility changes exhibit fat tails and are tail-distributed. This is evidenced by the data captured at the 95$^{\text{th}}$ percentile and 5$^{\text{th}}$ percentile of the distribution. We also record dispersions on a daily basis as evidenced by the standard deviation. Aside from changes in the overall emerging market volatility index, the changes in the other volatility indices are positively skewed and exhibit excess kurtosis. This means that frequent positive changes in the volatility indices except for VXEEM have occurred during the pandemic. Generally, volatility indices are countercyclical in nature and tend to increase during recession but are low in times of expansion [8]. In the time of the pandemic, the frequent positive increments can be attributable to increase in investor risk aversion as a result of increased fear and uncertainty. From the ADF test, we reject the null hypothesis of a unit at a 1% significance level.

The correlation coefficients and the variances indicate that IMF-1 dominates in all cases. Thus, we observe that the correlation-variance dominance minimizes with increasing levels of IMFs to the residual, which measures the deterministic long-term. More likely than not, spikes in implied volatility indices are mainly dominated by short-term disturbances. This probably explains the volatile nature of the daily changes in the indices as shown in Table 1. The mean period show the average frequencies of the respective IMFs [66]. The CMH presupposes that active portfolio rebalancing is a common feature of the pandemic. In line with this hypothesis and based on common features, we cluster IMF-1 to IMF-4 as the short-term (periods with high frequencies), IMF-5 to IMF-7 as the medium-term (medium frequencies) and the residuals imply the fundamental behavior of the changes in volatility series, the deterministic long-term trend. Thus, we classify the short-term as a period up to 15 days in the pandemic, mean periods above 15 days but below 144 days as the medium term. This is similar to the classification of Adam et al. [66] and Owusu Junior et al. [32].

4. Results and Discussion

This section of the study presents the results and its discussion. The analysis was conducted using the Rényi transfer entropy (RTE). First, we present the findings of the on the information flows between the emerging markets and the developed markets, VIX and VXEFA. Second, the study examines the information flows between BRIC volatility indices and the overall emerging market volatility index. RTE framework results in both negative (high risk) and positive (low risk) values. In the presence of increased uncertainty from a particular, the pairing enables us to examine whether diversification benefits exist for that market with the recipients. The ends of the blue bars represent critical levels from 1%–10%. In consequence, the blue bars should either be in the positive or negative regions to reject the null hypothesis of no information flow. This also implies that any overlap at the origin is insignificant.

4.1. Information Flows between Emerging Market Volatility Indices and VIX. Figure 2 presents the RTE plots representing the information flows between the VIX and the emerging markets across time horizons.

The dominance of the VIX in transmitting high risk information (leading the contagion) was asserted in the short

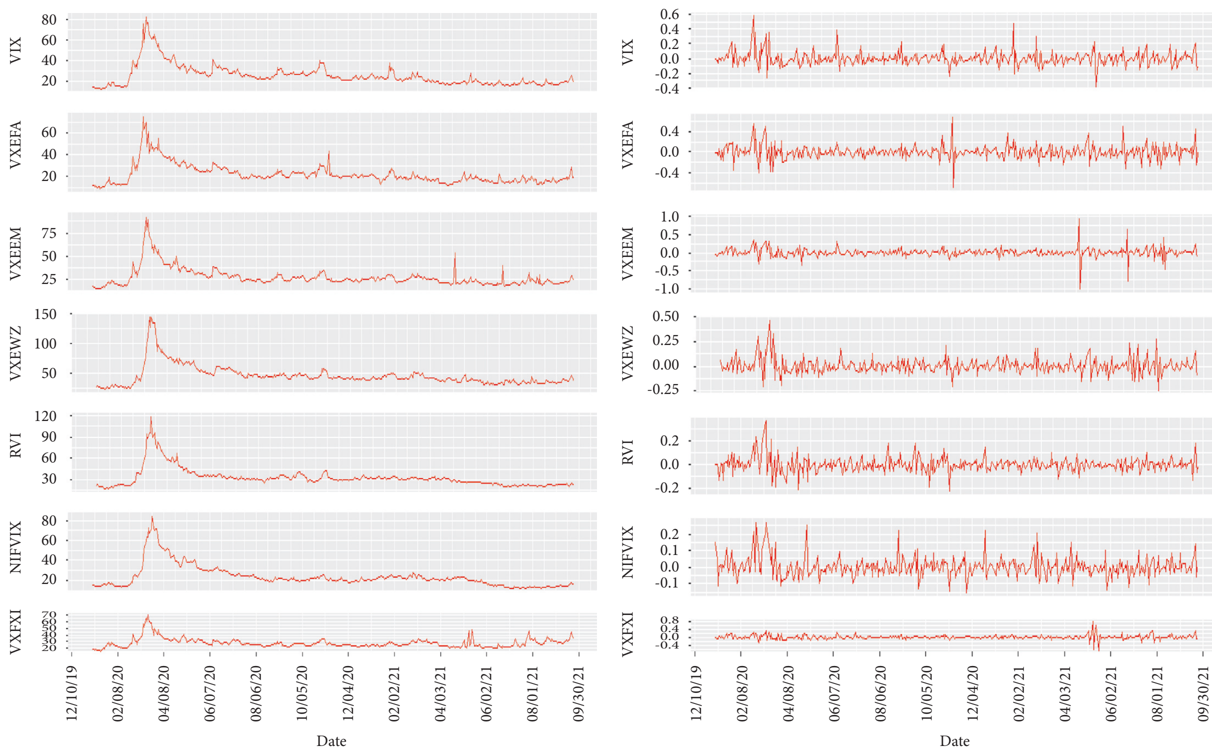

Figure 1: Plots of volatility indices (LHS) and changes in the indices (RHS).

Table 1: Descriptive statistics.

Variable	Mean	Q95	Q5	Std. dev.	Skewness	Kurtosis	ADF test
⊿VXEWZ	0.00086	0.12738	−0.09761	0.07530	1.2936	8.8771	−6.7416***
⊿RVI	0.00008	0.09798	−0.08509	0.06266	1.0571	9.5614	−6.4878***
⊿NIFVIX	0.00067	0.10155	−0.08217	0.05943	1.3286	7.0522	−5.302***
⊿VXFXI	0.00139	0.16807	−0.12508	0.10851	0.45390	18.524	−8.1013***
⊿VXEEM	0.00069	0.15747	−0.11671	0.12711	−0.38573	25.407	−8.3845***
⊿VXEFA	0.00113	0.19402	−0.17942	0.12874	0.39039	8.8125	−7.9595***
⊿VIX	0.00071	0.1640	−0.1140	0.09389	1.4350	10.152	−7.3102***

The summary statistics on the ln-changes (Δ) in the volatility indices daily are reported. The rows corresponds to implied volatility indices for stock markets in Brazil, Russia, India, China, overall emerging markets, developed markets, and the US market in the ascending order. The table reports the mean, 95th percentile, 5th percentile, skewness, Kurtosis and the ADF test of stationarity in the order from the second column to the seventh column respectively. ***, **, and * represent significance levels at 1%, 5% and 10%, respectively.

term with the US communicating significant negative information to the emerging market indices. The composite short-term results show a significant bidirectional flow of information between the RVI and the VIX. Moreover, we find that over the short-term, the VXFXI receives low risk information in the pandemic although not significant. This means that in the midst of increasing uncertainty which has increased the transmission of higher risks to emerging equities, a combination of assets from Brazil, Russia or India with the stocks from China may withstand shocks from the US, although gains from such diversification may be minimal.

The medium-term was denominated by negative transmissions of bidirectional information but mainly insignificant. While IMF-5 and IMF-6 give an indication that the emerging markets were dominating in terms of significant high risk information transmission, the composite view for the medium-term still showed complete domination of the VIX in transmitting negative information to emerging markets. Specifically, a significant bidirectional flow of information exists between VXEWZ, VXEEM and the VIX. Aside from NIFVIX, which was insignificant, the VIX transmitted significant high risk information to all the other emerging equities. Thus, the VIX also dominated the medium-term information flows. In the long-term, the study also reports a bidirectional flow of information, but these are mainly insignificant.

In common, the dynamics of information flows in both the short- and medium-terms underscore the superiority of the VIX in transmitting contagion to emerging markets. The superiority of the information content of the VIX has been well documented in the extant literature [65, 67–69]. The coronavirus which has affected cross-border movements of goods and capital significantly affecting trade and since emerging markets are tied to USA mainly through underlying trade and investments, it creates the conditions for shock transmission among financial markets. The direction

Table 2: Description of IMFs and residuals for the volatility changes.

Index	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF6	IMF 7	Residual
⊿VXEWZ								
μ	2.858	4.975	6.948	12.594	22.389	40.3	57.57	
ρ	0.7547***	0.3728***	0.4195***	0.3135***	0.1687***	0.1278***	0.0444	0.0729*
σ_1^2	0.6573	0.1222	0.0652	0.047	0.0814	0.0275	0.0023	0.0235
σ_2^2	0.6573	0.1222	0.0652	0.047	0.0814	0.0275	0.0023	0.0235
⊿RVI								
μ	2.7793	4.9753	6.6066	11.85	21.2105	40.3	67.167	
ρ	0.7461***	0.4881***	0.3450***	0.3404***	0.2244***	0.2103***	0.1277***	0.0216***
σ_1^2	0.6274	0.0994	0.0529	0.0746	0.0197	0.0315	0.0079	0.0148
σ_2^2	0.6274	0.0994	0.0529	0.0746	0.0197	0.0315	0.0079	0.0148
⊿NIFVIX								
μ	2.9416	4.7976	7.1964	12.2121	22.3889	33.583	80.6	
ρ	0.7183***	0.4726***	0.3698***	0.2578***	0.2232***	0.1904***	0.1507***	0.1233***
σ_1^2	0.5931	0.0876	0.0607	0.0672	0.1453	0.0080	0.0108	0.0636
σ_2^2	0.5931	0.0876	0.0607	0.0672	0.1453	0.0080	0.0108	0.0636
⊿VXFXI								
μ	2.723	4.7411	6.397	13.433	22.389	36.636	57.57	
ρ	0.8242***	0.4231***	0.283***	0.2058***	0.0855**	0.0636	0.0398	0.0403
σ_1^2	0.7392	0.1393	0.0555	0.0415	0.0305	0.0078	0.0014	0.0045
σ_2^2	0.7392	0.1393	0.0555	0.0415	0.0305	0.0078	0.0014	0.0045
⊿VXEEM								
μ	2.723	4.915	6.106	11.853	22.389	44.778	67.167	
ρ	0.7281***	0.3901***	0.2953***	0.1690***	0.0872**	0.0740*	0.0153	0.0371
σ_1^2	0.8295	0.2227	0.0957	0.0428	0.0345	0.0063	0.0052	0.0076
σ_2^2	0.8295	0.2227	0.0957	0.0428	0.0345	0.0063	0.0052	0.0076
⊿VXEFA								
μ	2.687	4.914	6.948	12.594	23.706	36.636	100.75	
ρ	0.7999***	0.4063***	0.3088***	0.195***	0.0753*	0.0975**	0.0357	0.0431
σ_1^2	0.7497	0.1596	0.0631	0.0318	0.0427	0.0154	0.0031	0.0050
σ_2^2	0.7497	0.1596	0.0631	0.0318	0.0427	0.0154	0.0031	0.0050
⊿VIX								
μ	2.760	4.8552	6.3968	13.0	21.2105	44.7778	80.6	
ρ	0.7449***	0.4396***	0.3914***	0.2030***	0.1155***	0.1319***	0.0605	0.0646*
σ_1^2	0.6539	0.1407	0.0673	0.1037	0.1169	0.0177	0.0079	0.0028
σ_2^2	0.6539	0.1407	0.0673	0.1037	0.1169	0.0177	0.0079	0.0028

The features of the decomposed data. We report the mean period (μ) measured by the total number of points divided by number of peaks. This means that the value of the μ is indirectly related with the level of frequency. The Pearson correlation coefficients (ρ) are also reported computed as the correlation between each IMF and the original/observed volatility indices. The variance proportion of each IMF and the residue to the variance in the original data (σ_1^2) as well as the variance proportion of each IMF to the total variance in the decomposed data (σ_2^2). The latter, should mainly corroborate with σ_1^2.

of the shocks which is largely from the VIX can be presumed that these emerging markets are more dependent on the USA for trade, although it bilateral (evidenced by the bidirectional flow of information occurring at some frequencies). Hence, it is likely the shocks to trade flows as a result of the coronavirus pandemic might have exacerbated the contagion, resulting in high risk transmission to emerging equities. Moreover, since active portfolio rebalancing should be a regular feature of international USA investors in the short and medium term due to the COVID-19 pandemic, a recalibration of portfolios will result in increased activity by USA investors who may be having equities from these emerging markets in their portfolios or who may want to invest in emerging equities as stocks from emerging markets are regarded as segmented stocks, eventually increasing the risk of contagion in those markets. Our findings in the short and medium-terms which confirms the dominance of the VIX in transmitting high risk information is not shocking because the VIX is also regarded as the overall investor fear gauge [70–72]. Thus, the performance of the USA market has been a predictor of stock returns in other countries including emerging economies. The findings in the short- and medium-term corroborates with studies that document that the US stock market exhibit significant volatility and mean spill-over to emerging stock markets [7, 8, 73–76]. Similarly, Bhattarai et al. [28] and Horvath and Zhong [29] documented that emerging markets are susceptible to shocks from the USA with the latter adducing empirical evidence to support that the channel of the external shock to the emerging countries is fundamentally through their stock markets.

In the long-term, we document that the VIX and the emerging equities transmit high risk information between each other, but it is not statistically significant. In this horizon, we expect changes in fear between the USA and emerging equities to be largely influenced by

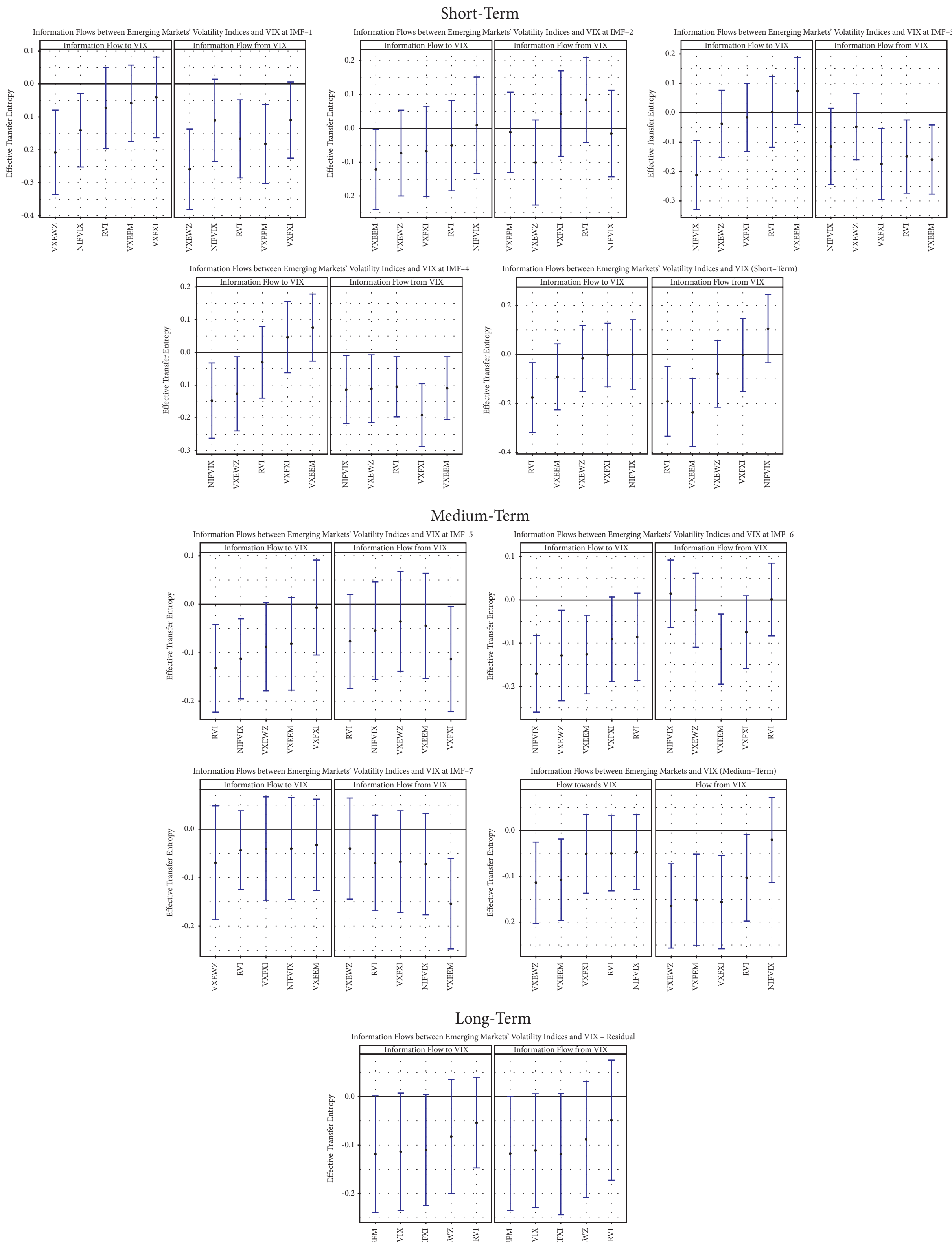

Figure 2: Information flows between emerging market volatility indices and VIX.

country-specific factors and other underlying fundamentals. Our findings are contrary to the study of Dutta [74] who finds significant long-run relationship between the volatility indices of the USA stock market and that of China and Brazil. This study was not conducted in a crisis period and did not attempt to deal with the noise, non-linearities and tail-dependence in the financial time series data.

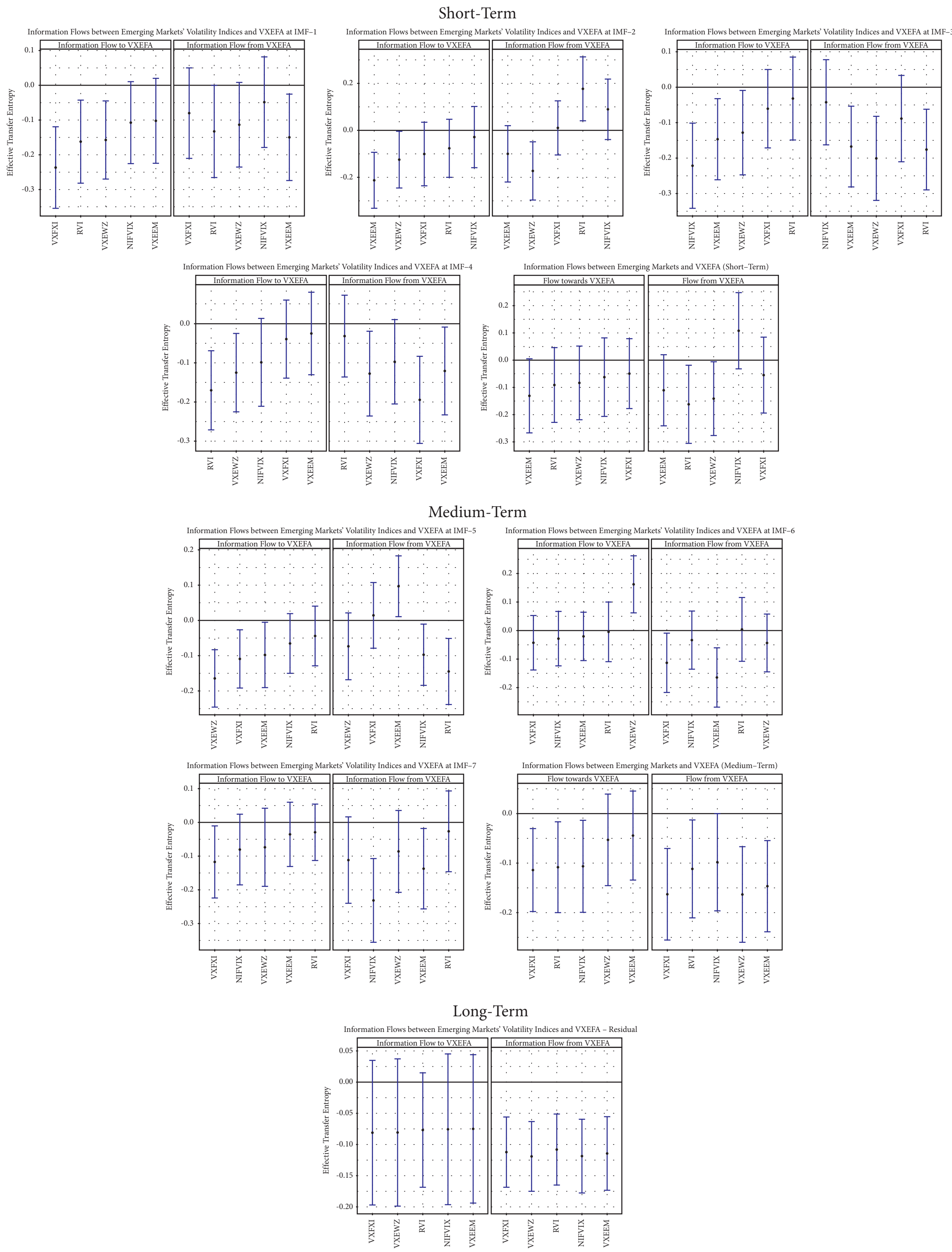

Figure 3: Information flows between emerging market volatility indices and VXEFA.

4.2. Information Flows between Emerging Market Volatility Indices and VXEFA. Having examined the information flows between the emerging markets and VIX, we also quantify the information flows between the emerging market equities and VXEFA as shown in Figure 3. The VXEFA measures the implied volatility index for 24 developed markets, excluding the US.

In the short-term, we observe from IMF-1 to IMF-4 varying degree and nature of information flows with

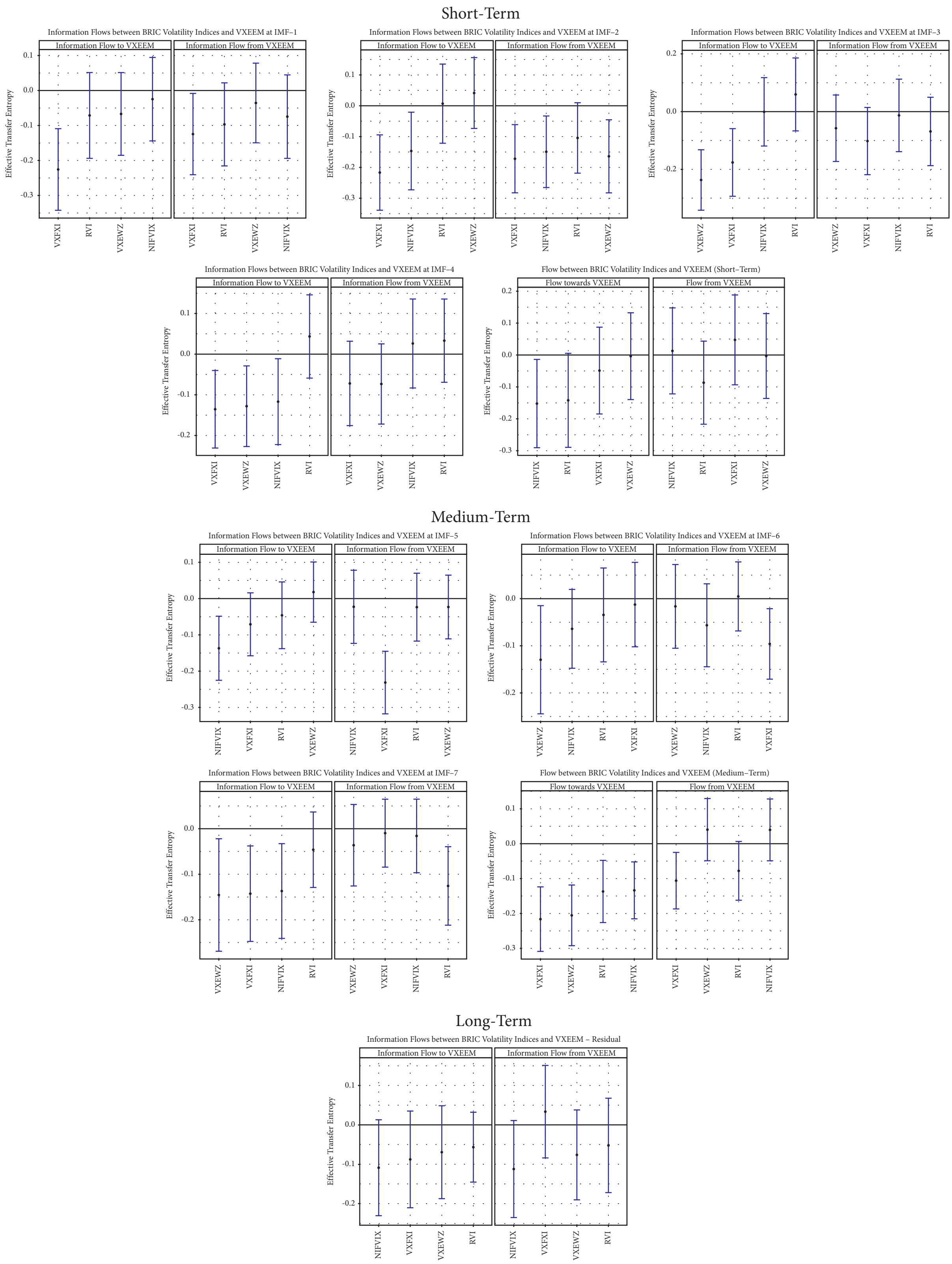

FIGURE 4: Information flows between BRIC volatility indices and VXEEM.

diversification potentials. While, we find information linkages in the short-term to be largely insignificant, we document at IMF-2 that a combination of stocks from the Brazil and Russia can absorb shocks from the developed markets. Specifically, at IMF-2, we observe that RVI is a significant positive recipient of shocks from the VXEFA while VXEWZ is a significant negative recipient. Overall, we find that in the short-term, the VXEFA dominates the emerging equities in

Table 3: Information flows between the VIX and emerging markets volatility indices.

Direction of information flow	IMF1 ETE (SE)	IMF2 ETE (SE)	IMF3 ETE (SE)	IMF4 ETE (SE)	AST ETE (SE)	IMF5 ETE (SE)	IMF6 ETE (SE)	IMF7 ETE (SE)	AMT ETE (SE)	Residual/LT ETE (SE)
VXEWZ -> VIX	−0.2076*** (0.0782)	−0.0735 (0.0771)	−0.0380 (0.0698)	−0.1270* (0.0686)	−0.0156 (0.0821)	−0.0878 (0.0587)	−0.1282** (0.0637)	−0.0879 (0.0554)	−0.1140** (0.0536)	−0.0831 (0.0714)
VIX -> VXEWZ	−0.2595*** (0.0747)	−0.1017 (0.0766)	−0.0483 (0.0684)	−0.1113* (0.0630)	−0.0792 (0.0834)	−0.0387 (0.0650)	−0.0238 (0.0519)	−0.0354 (0.0624)	−0.165*** (0.0556)	−0.0888 (0.0725)
RVI -> VIX	−0.0730** (0.0743)	−0.0511 (0.0814)	0.0019 (0.0730)	−0.0303 (0.0668)	−0.1759** (0.0868)	−0.1316** (0.0553)	−0.08565 (0.0614)	−0.0433 (0.0492)	−0.050 (0.0450)	−0.0541 (0.0568)
VIX -> RVI	−0.1667** (0.0722)	0.0842 (0.0763)	−0.149** (0.0753)	−0.1059* (0.0557)	−0.1919** (0.0870)	−0.0762 (0.0588)	0.0010 (0.0511)	−0.0695 (0.0599)	−0.1033* (0.0572)	−0.0489 (0.0754)
NIFVIX -> VIX	−0.1401** (0.068)	0.0091 (0.086)	−0.2122*** (0.0717)	−0.1477** (0.0698)	−0.0003 (0.0863)	−0.1123** (0.0501)	−0.1710*** (0.0540)	−0.0398 (0.0640)	−0.0477 (0.0497)	−0.1140 (0.0738)
VIX -> NIFVIX	−0.1099 (0.0763)	−0.016 (0.0777)	−0.1149 (0.0789)	−0.1134* (0.0629)	0.1061 (0.0847)	−0.0545 (0.0614)	0.0139 (0.0475)	−0.0721 (0.0637)	−0.0204 (0.0561)	−0.1116 (0.0713)
VXFXI -> VIX	−0.0405 (0.0745)	−0.0682 (0.0812)	−0.0160 (0.070)	0.0463 (0.0658)	−0.0024 (0.0794)	−0.0066 (0.0596)	−0.0910 (0.0594)	−0.0406 (0.0653)	−0.0509 (0.0522)	−0.1103 (0.0696)
VIX -> VXFXI	−0.1095 (0.0704)	0.0429 (0.0768)	−0.1744** (0.0734)	−0.1917*** (0.0585)	−0.0017 (0.0912)	−0.1127* (0.0661)	−0.0751 (0.0512)	−0.0667 (0.0637)	−0.1566** (0.0618)	−0.1190 (0.0761)
VXEEM -> VIX	−0.0577 (0.0702)	−0.1222* (0.0722)	0.0734 (0.0697)	0.0757 (0.0620)	−0.0920 (0.0822)	−0.0815 (0.0582)	−0.1262** (0.0553)	−0.0323 (0.0576)	−0.1078** (0.0540)	−0.1186 (0.0731)
VIX -> VXEEM	−0.1825** (0.0730)	−0.0118 (0.0722)	−0.1592** (0.0714)	−0.1100* (0.0581)	−0.2377*** (0.0845)	−0.0443 (0.0660)	−0.1134** (0.0494)	−0.1538*** (0.0566)	−0.1516** (0.0605)	−0.1176 (0.0716)

Note. ETE,and SE denote effective transfer entropy estimate and standard error. AST means aggregate short term, and AMT also represents aggregate medium term. standard errors in parenthesis.*, **, and *** indicate significance at 10%, 5% and 1% levels respectively.

Table 4: Information flows between the VXEFA and emerging markets volatility indices.

Direction of information flow	IMF1 ETE (SE)	IMF2 ETE (SE)	IMF3 ETE (SE)	IMF4 ETE (SE)	AST ETE (SE)	IMF5 ETE (SE)	IMF6 ETE (SE)	IMF7 ETE (SE)	AMT ETE (SE)	Residual/LT ETE (SE)
VXEWZ ->	−0.1571**	−0.1249*	−0.1284*	−0.1253**	−0.0843	−0.1645***	0.1619***	−0.0732	−0.0532	−0.0808
VXEFA	(0.0684)	(0.0735)	(0.0725)	(0.0609)	(0.0820)	(0.0494)	(0.0608)	(0.0705)	(0.0563)	(0.0718)
VXEFA ->	−0.1137	−0.1722**	−0.2004***	−0.1278*	−0.1420*	−0.0733	−0.0433	−0.0855	−0.1637***	−0.1192***
VXEWZ	(0.0741)	(0.0755)	(0.0721)	(0.0658)	(0.0825)	(0.0577)	(0.0617)	(0.0738)	(0.0589)	(0.0339)
RVI -> VXEFA	−0.1621**	−0.07628	−0.0314	−0.1706***	−0.0920	−0.04377	−0.0049	−0.0292	−0.1085*	−0.07695
	(0.0727)	(0.0757)	(0.0711)	(0.0614)	(0.0836)	(0.0512)	(0.0636)	(0.0508)	(0.0558)	(0.0557)
VXEFA -> RVI	−0.13291	0.17706**	−0.1758**	−0.0321	−0.16287*	−0.1443**	0.0045	−0.0265	−0.1119*	−0.1081***
	(0.0808)	(0.0827)	(0.0691)	(0.0632)	(0.0874)	(0.0570)	(0.0679)	(0.07294)	(0.0603)	(0.0345)
NIFVIX -> VXEFA	−0.1073	−0.0286	−0.2213***	−0.0989	−0.0624	−0.0657	−0.0283	−0.0801	−0.1065*	−0.07563
	(0.0719)	(0.0794)	(0.0734)	(0.0682)	(0.0876)	(0.0514)	(0.0582)	(0.0639)	(0.0565)	(0.0738)
VXEFA -> NIFVIX	−0.0485	0.0899	−0.0418	−0.0972	0.1077	−0.0972	−0.0338	−0.2313***	−0.0980	−0.1185***
	(0.0794)	(0.0783)	(0.0732)	(0.0654)	(0.0851)	(0.0529)	(0.0621)	(0.0757)	(0.0598)	(0.0359)
VXFXI -> VXEFA	−0.2374***	−0.1003	−0.0598	−0.0399	−0.0501	−0.1089**	−0.0424	−0.117*	−0.1138**	−0.0811
	(0.0715)	(0.0822)	(0.0673)	(0.06047)	(0.0779)	(0.0502)	(0.0579)	(0.0651)	(0.0510)	(0.070)
VXEFA -> VXFXI	−0.0803	0.0106	−0.0883	−0.1947***	−0.0554	0.0140	−0.1127*	−0.1114	−0.1631***	−0.1122***
	(0.0792)	(0.0699)	(0.0741)	(0.0677)	(0.0847)	(0.0565)	(0.0632)	(0.0777)	(0.0562)	(0.0342)
VXEEM -> VXEFA	−0.1022	−0.2131***	−0.1466**	−0.0255	−0.1312	−0.0974	−0.0203	−0.0349	−0.0443	−0.0748
	(0.0743)	(0.0724)	(0.0696)	(0.0641)	(0.0825)	(0.0563)	(0.0516)	(0.0578)	(0.0547)	(0.0722)
VXEFA -> VXEEM	−0.1498**	−0.09969	−0.1673**	−0.1210*	−0.1107	0.0967	−0.1647***	−0.1371*	−0.1468***	−0.1144***
	(0.0758)	(0.0730)	(0.0696)	(0.0681)	(0.0794)	(0.0522)	(0.0634)	(0.0723)	(0.0562)	(0.0358)

Note. ETE and SE denote effective transfer entropy estimate and standard error. AST means aggregate short term, and AMT also represents aggregate medium term. Standard errors in parenthesis.*, **, and *** indicate significance at 10%, 5% and 1% levels respectively.

Table 5: Information flows between BRIC volatility indices and overall emerging market volatility index.

Direction of information flow	IMF1 ETE (SE)	IMF2 ETE (SE)	IMF3 ETE (SE)	IMF4 ETE (SE)	AST ETE (SE)	IMF5 ETE (SE)	IMF6 ETE (SE)	IMF7 ETE (SE)	AMT ETE (SE)	Residual/LT ETE (SE)
VXEWZ -> VXEEM	−0.0922 (0.0744)	0.0411 (0.0698)	−0.2373*** (0.0637)	−0.1287** (0.0603)	−0.0038 (0.0825)	0.0182 (0.0507)	−0.1296* (0.070)	−0.1459* (0.0750)	−0.2055*** (0.0530)	−0.0690 (0.0717)
VXEEM -> VXEWZ	−0.0323 (0.0743)	−0.1641** (0.0721)	−0.0580 (0.0699)	−0.0735 (0.060)	−0.0035 (0.0807)	−0.0227 (0.0532)	−0.0162 (0.0541)	−0.0364 (0.0543)	0.0402 (0.0544)	−0.0761 (0.0693)
RVI -> VXEEM	−0.0705 (0.0734)	0.0066 (0.0781)	0.0594 (0.0769)	0.0431 (0.0624)	−0.1425 (0.0892)	−0.0458 (0.0560)	−0.0342 (0.0604)	−0.0463 (0.0501)	−0.1367** (0.0541)	−0.0559 (0.0540)
VXEEM -> RVI	−0.0991 (0.0734)	−0.1042 (0.0695)	−0.0687 (0.0718)	0.0329 (0.0625)	−0.0877 (0.0790)	−0.0233 (0.0570)	0.0047 (0.0446)	−0.1255** (0.0523)	−0.0774 (0.0512)	−0.1081 (0.0729)
NIFVIX -> VXEEM	−0.0127 (0.0704)	−0.1466* (0.0766)	−0.0008 (0.0720)	−0.1173* (0.0642)	−0.1530* (0.0841)	−0.1371*** (0.0540)	−0.064 (0.0508)	−0.1372** (0.0631)	−0.1333*** (0.0496)	−0.0518 (0.0739)
VXEEM -> NIFVIX	−0.0885 (0.0723)	−0.1496** (0.0708)	−0.0132 (0.0762)	0.0259 (0.0666)	0.0121 (0.0851)	−0.0224 (0.0614)	−0.0564 (0.0535)	−0.0160 (0.04886)	0.0401 (0.0538)	−0.1120 (0.0751)
VXFXI -> VXEEM	−0.2354*** (0.0646)	−0.2175*** (0.0743)	−0.1762** (0.0709)	−0.1359** (0.0583)	−0.0496 (0.0827)	−0.0708 (0.0530)	−0.01231 (0.0544)	−0.1425** (0.0638)	−0.2167*** (0.0563)	−0.0872 (0.0745)
VXEEM -> VXFXI	−0.1272* (0.0737)	−0.1719** (0.0672)	−0.1022 (0.0709)	−0.0720 (0.0632)	0.0467 (0.0857)	−0.2315*** (0.0528)	−0.0957 (0.0455)	−0.00983 (0.0453)	−0.1058*** (0.04943)	0.0339 (0.0715)

Note. ETE and SE denote effective transfer entropy estimate and standard error. AST means aggregate short term, and AMT also represents aggregate medium term. Standard errors in parenthesis.*, **, and *** indicate significance at 10%, 5% and 1% levels respectively.

information transmission. The VXEFA transmits high risk information while information flow from emerging equities although high risk are insignificant. Noticeably, we also find that the NIFVIX is a positive recipient of information from the VXEFA although this is insignificant. In consequence, albeit the stocks from India can be paired against any of the emerging equities in the pandemic to withstand short-run shocks from the VXEFA, the gains from such portfolios are also minimal given that the low risk information flows to the NIFVIX are not significant.

In the medium-term, we document that except for equity markets in Brazil and the overall emerging market which transmit insignificant negative shocks to the VXEFA, there exist a significant bidirectional negative information spillovers between each of Russia, India, China and the developed markets. We attribute these findings to increased trade and investments between the developed equities in the Middle East and Europe and the emerging markets. These economies largely depend on themselves for cross-border trade and investments due to proximity and other benefits, which might have resulted in enormous integration. This makes high risks intensified due the shocks in cross-border trade from the coronavirus pandemic easily transmissible. The findings corroborate with the study of Badshah et al. [8], Al Nasser and Hajilee [77] and Todea [78].

4.3. Information Flows between BRIC Volatility Indices and VXEEM. From Figure 4, we find that BRIC economies often transmit significant high risk information to the overall emerging market volatility index (VXEEM) in the short-term while information from the VXEEM to the BRIC volatility indices are not significant. Over the short-term, we expect NIFVIX and VXFXI to be recipients of positive information from the VXEEM in the pandemic although it is not statistically significant. In the medium-term, BRIC economies continue to show maximum dominance by transmitting significant high risk information to the overall index for emerging markets. At the same time, India maintains its status as a recipient of positive but insignificant information. The positive and insignificant information is also documented for the Brazilian stock market as well. In the long-term, we observe that except for the VXFXI which receives insignificant negative information from the VXEEM, there exist a bidirectional flow of information between the BRIC equity markets and the overall emerging market index.

BRIC equity markets in the short and medium term have been shown to dominate in volatility transmissions especially from China. The dominion of BRIC economies is not shocking because BRIC countries are the engine of economic growth in emerging economies [79]. Thus, shocks from the financial markets of these economies should have implications on the financial structure of the overall emerging market. Mostly in the short-term and frequently in the medium-term, the study also documents a bi-directional flow of significant and high risk information between the VXFXI to the VXEEM with the VXFXI dominating in terms of information intensity. This may be attributable to the strength of the economic power of China and the growing financial structure of the Chinese economy. China being one of the biggest export partners to emerging economies could also underlie the strength of the VXFXI in the contagion transmission during the pandemic. While political and macroeconomic differences exist between China and the emerging economies, several studies show that contagion could be easily spread among countries closely tied with international trade than macroeconomic policies [80–82].

Moreover, we find that in the short and medium-term, Russia, Brazil, and India are frequent transmitters of positive but insignificant news. This partly underlies the differences in the contribution of the emerging markets to the overall emerging market index. This also paves benefits for investors to diversify in the short-term with these stocks and the overall market index although the benefits from such strategies are minimal given that the opportunities are not persistent throughout the short-term periods and also due to the insignificance in the information flows. The findings divulge that opportunities for diversification even in short-term must be considered with care and investors must be very active in portfolio construction, in line with the competitive market hypothesis [32]. Further, investors need to adapt to changing investment opportunities in the short-term, consistent with the adaptive market hypothesis [26, 27]. For instance, as low as 7 days in the short-term, Russia and Brazil can diversify with the VXEFA in the midst of increasing contagion and shocks emanating from China. After this period until 12 days in the short-term, Russia and India but not Brazil can offer such minimal benefits.

The heterogeneous nature of the market opportunities is also seen in the medium-term, where eventually, there is immense contagion emanating from BRIC economies to the VXEFA. However, the ability of the VXEFA to transmit high risk information is low in such horizon with Brazil and India receiving insignificant positive information. In the long-term, we presume that expected growth from other emerging economies in Europe, Asia, and Latin America may diminish the extent to which BRIC economies can transmit high risk information, minimizing the contagion to the overall emerging market volatility index, thus, accounting for the insignificance in the information flows. No, diversification benefits exists in the long-term between the VXEFA and BRIC economies. It can be assumed that in the long-term, the VXEFA should have the complete information content of BRIC equity volatilities, thereby eroding such diversification benefits. In parallel, country-specific variables could be an important source of risk aversion rather than industry-specific factors in each emerging market in the long-term, making equity price volatilities vary for each emerging market and minimizing the extent to which contagion can be transmitted. The findings are in line with the studies of Eun and Lee [18] and Phylaktis and Xia [19].

4.4. Summary of Findings. The study presents the summary findings in Tables 3–5 for information flows between the emerging markets and the VIX, the emerging markets and the VXEFA and the between BRIC countries and VXEEM respectively.

5. Conclusion and Policy Implications

The flight to safety triggered by the COVID-19 pandemic has accelerated the search for segmented markets to minimize investor losses. This has ignited discussions on whether emerging equity markets have achieved full integration due to increased underlying cross-border trade and investments with developed markets, thereby eliminating all gains from diversification. In this regard, an assessment of the degree of contagion between emerging markets and developed markets in the light of the pandemic can bring clarity to the debate on whether emerging equities should still be classified as segmented. Aside from this, a well-structured empirical discourse can be useful to international investors alike [83].

Corollary to this, we employ implied volatility indices, which capture investor fear and sentiments about future stock market activity. This is because discussions on market integration and contagion are captured much faster and clearer through volatility volatilities than stock returns. Specifically, we use the VIX, VXEFA, VXEWZ, RVI, NIFVIX, VXFXI, and VXEEM which depicts implied volatility indices from the USA stock market, developed markets (excluding the USA), Brazil, Russia, India, China, and overall emerging market index, respectively. In line with the heterogeneous, adaptive and competitive market hypotheses, we decompose the volatility changes into intrinsic time using the CEEMDAN. Further we clustered the IMFs using the mean periods into short-, medium-, and long-term. Subsequent to this, we apply Rényi's variant of transfer entropy which deals with tail-dependence and non-linearities which exist in changes in volatility indices.

Regarding the flow of information between volatility indices of BRIC economies and that of the overall emerging market volatility index, we document significant high risk information usually emanating from BRIC countries to the emerging market index both the short- and medium-term. In the long–term, we find the existence of bidirectional flow of negative information but these are largely insignificant. As regards the information flows between emerging markets and the developed equity markets, we adduce evidence to support both bi-directional and uni-directional flow of high risk information and low risk information from emerging equity markets and from the developed markets. We find that the transmission of high risk information is largely dominated by the developed markets (VIX and VXEFA).

In common, we note that a high level of contagion from developed equity markets exist in the pandemic with emerging equities which diminishes the benefits of diversification during the pandemic. Nonetheless, investors can take advantage of the minimal benefits that exists in both markets by shielding against adverse shocks from the developed markets with a combination of stocks from India and other equities in the emerging markets in the short-term. Moreover, portfolios comprising equities from Russia and Brazil also offer immunity to shocks from the VXEFA, in the very short-term, approximately within 5 days. In this regard, our findings divulge that international investors who seek to diversify with equities from BRIC economies must pay attention to shocks from the implied volatility indices of BRIC countries, the VIX and the VXEFA to undertake active portfolio rebalancing in the short-term. The findings also have important policy implications.

To minimize the impact of the COVID-19 which has opened the floodgates for financial harm and contagion among equity markets, policymakers in the developed economies and emerging markets must develop a rapid response mechanism to dealing with the uncertainty and fear among investors. The implementation of fiscal and monetary policies to deal with the economic impact of the pandemic can minimize investor fear. Policymakers in emerging economies must also reduce policy inconsistencies and take steps to achieve export and import diversification from developed markets to minimize the extent to which shocks to trade and investments from developed countries can cause financial harm.

Although the Rényi entropy is robust and deals with most of the inherent problems in time series, the findings must be assimilated with caution. We note that the time zone factor can affect the spread of contagion in the pandemic, which is considered as a caveat for this study. Similar trading times mean greater synchronicity, allowing markets to acquire innovations and receive external shocks simultaneously. Markets that do not have the same trading time zone are exposed to non-synchronism which can lead to an underestimation of the extent of linkages. Further studies can test the lag effects to circumvent the problems of non-synchronicity. Additionally, the time and frequency nexus among the variables could be explored to divulge both structural events adaptability and investors' horizons heterogeneity as in the case of bi-wavelet, partial wavelet, Baruník and Křehlík [84] approaches, etc., [85–88].

Data Availability

The data used to support this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interests.

References

[1] B. N. Ashraf, N. Qian, and Y. V. Shen, "The impact of trade and financial openness on bank loan pricing: evidence from emerging economies," *Emerging Markets Review*, vol. 47, Article ID 100793, 2021.

[2] K. P. Lim and J. H. Kim, "Trade openness and the informational efficiency of emerging stock markets," *Economic Modelling*, vol. 28, no. 5, pp. 2228–2238, 2011.

[3] S. H. law and M. S. habibullah, "The determinants of financial development: institutions, openness and financial liberalisation," *South African Journal of Economics*, vol. 77, no. 1, pp. 45–58, 2009.

[4] T. H. Le, J. Kim, and M. Lee, "Institutional quality, trade openness, and financial sector development in Asia: an empirical investigation," *Emerging Markets Finance and Trade*, vol. 52, no. 5, pp. 1047–1059, 2016.

[5] I. U. Badshah, "Volatility spillover from the fear index to developed and emerging markets," *Emerging Markets Finance and Trade*, vol. 54, no. 1, pp. 27–40, 2018.
[6] Y. C. Lu, Y. C. Wei, and C. W. Chang, "Nonlinear dynamics between the investor fear gauge and market index in the emerging taiwan equity market," *Emerging Markets Finance and Trade*, vol. 48, no. sup1, pp. 171–191, 2012.
[7] G. Sarwar and W. Khan, "The effect of US stock market uncertainty on emerging market returns," *Emerging Markets Finance and Trade*, vol. 53, no. 8, pp. 1796–1811, 2017.
[8] I. Badshah, S. Bekiros, B. M. Lucey, and G. S. Uddin, "Asymmetric linkages among the fear index and emerging market volatility indices," *Emerging Markets Review*, vol. 37, pp. 17–31, 2018.
[9] G. Bekaert and C. R. Harvey, *Emerging Equity Markets in a Globalizing World. SSRN Scholarly Paper ID 2344817*, Social Science Research Network, Rochester, NY, USA, 2014.
[10] G. BekaertBekaert, C. R. HarveyHarvey, C. T. LundbladLundblad, and S. Siegel, "What segments equity markets?" *Review of Financial Studies*, vol. 24, no. 12, pp. 3841–3890, 2011.
[11] A. Akbari, L. Ng, and B. Solnik, "Drivers of economic and financial integration: a machine learning approach," *Journal of Empirical Finance*, vol. 61, pp. 82–102, 2021.
[12] G. Bekaert and C. R. Harvey, "Emerging Equity Markets in a Globalizing World," , Article ID 2344817, 2017.
[13] D. Muller, "Emerging markets–powerhouse of global growth," *Ashmore Market Commentary*, vol. 2, 2018.
[14] O. Bouslama and O. B. Ouda, "The benefit of international equity diversification: the â€˜ 1/nâ€™ diversification rule," *International Journal of Empirical Finance*, vol. 4, no. 1, pp. 59–68, 2015.
[15] P. Owusu Junior, I. Alagidede, and G. Tweneboah, "Shape-shift contagion in emerging markets equities: evidence from frequency- and time-domain analysis," *Economics and Business Letters*, vol. 9, no. 3, pp. 146–156, 2020.
[16] P. Owusu JuniorOwusu Junior and I. Alagidede, "Risks in emerging markets equities: time-varying versus spatial risk analysis," *Physica A: Statistical Mechanics and Its Applications*, vol. 542, Article ID 123474, 2020.
[17] P. Owusu Junior, I. P. Alagidede, and A. K. Tiwari, "On the elicitability and risk model comparison of emerging markets equities," *Mathematical and Computational Applications*, vol. 26, no. 3, p. 63, 2021.
[18] C. S. Eun and J. Lee, "Mean-variance convergence around the world," *Journal of Banking & Finance*, vol. 34, no. 4, pp. 856–870, 2010.
[19] K. Phylaktis and L. Xia, "Equity market comovement and contagion: a sectoral perspective," *Financial Management*, vol. 38, no. 2, pp. 381–409, 2009.
[20] Š. Lyócsa and E. Baumöhl, "Similarity of emerging market returns under changing market conditions: markets in the ASEAN-4, Latin America, Middle East, and BRICs," *Economic Systems*, vol. 39, no. 2, pp. 253–268, 2015.
[21] R. Kirchner, R. Giucci, and V. Kravchuk, *Improving the Framework of Credit Bureaus' Operations: Key Recommendations*, Berlin Economics Report, Berlin, Germany, 2012.
[22] X. Zhang, Q. Zhang, D. Chen, and J. Gu, "Financial integration, investor protection and imbalanced optimistically biased information timeliness in emerging markets," *International Review of Financial Analysis*, vol. 64, pp. 38–56, 2019.
[23] D. Holtbrügge and A. Baron, "Market entry strategies in emerging markets: an institutional study in the BRIC countries," *Thunderbird International Business Review*, vol. 55, no. 3, pp. 237–252, 2013.
[24] W. Mensi, S. Hammoudeh, and S. H. Kang, "Risk spillovers and portfolio management between developed and BRICS stock markets," *The North American Journal of Economics and Finance*, vol. 41, pp. 133–155, 2017.
[25] P. Owusu Junior, A. M. Adam, E. Asafo-Adjei, E. Boateng, Z. Hamidu, and E. Awotwe, "Time-frequency domain analysis of investor fear and expectations in stock markets of BRIC economies," *Heliyon*, vol. 7, no. 10, Article ID e08211, 2021.
[26] G. Sharma, P. Kayal, and P. Pandey, "Information linkages among BRICS countries: empirical evidence from implied volatility indices," *Journal of Emerging Market Finance*, vol. 18, no. 3, pp. 263–289, 2019.
[27] S. G. Calvo and C. M. Reinhart, *Capital Flows to Latin America: Is There Evidence of Contagion Effects?*, 1996.
[28] S. Bhattarai, A. Chatterjee, and W. Y. Park, "Global spillover effects of US uncertainty," *Journal of Monetary Economics*, vol. 114, pp. 71–89, 2020.
[29] J. Horvath and J. Zhong, "Unemployment dynamics in emerging countries: monetary policy and external shocks," *Economic Modelling*, vol. 76, pp. 31–49, 2019.
[30] R. Dornbusch, Y. C. Park, and S. Claessens, "Contagion: understanding how it spreads," *The World Bank Research Observer*, vol. 15, no. 2, pp. 177–197, 2000.
[31] S. Gunay, *A New Form of Financial Contagion: Covid-19 and Stock Market Responses*, 2020.
[32] P. Owusu Junior, S. Frimpong, A. M. Adam et al., "COVID-19 as information transmitter to global equity markets: evidence from CEEMDAN-based transfer entropy approach," *Mathematical Problems in Engineering*, vol. 2021, Article ID 8258778, 19 pages, 2021.
[33] S. D. Bekiros, "Contagion, decoupling and the spillover effects of the US financial crisis: evidence from the BRIC markets," *International Review of Financial Analysis*, vol. 33, pp. 58–69, 2014.
[34] P. R. Masson, T. Bayoumi, and H. Samiei, "International evidence on the determinants of private saving," *The World Bank Economic Review*, vol. 12, no. 3, pp. 483–501, 1998.
[35] K. Malik, S. Sharma, and M. Kaur, "Measuring contagion during COVID-19 through volatility spillovers of BRIC countries using diagonal BEKK approach," *Journal of Economics Studies*, vol. 49, no. 2, pp. 227–242, 2021.
[36] Y. Peng and W. L. Ng, "Analysing financial contagion and asymmetric market dependence with volatility indices via copulas," *Annals of Finance*, vol. 8, no. 1, pp. 49–74, 2012.
[37] A. Dutta, J. Nikkinen, and T. Rothovius, "Impact of oil price uncertainty on Middle East and African stock markets," *Energy*, vol. 123, pp. 189–197, 2017.
[38] E. Boateng, A. M. Adam, and P. O. Junior, "Modelling the heterogeneous relationship between the crude oil implied volatility index and African stocks in the coronavirus pandemic," *Resources Policy*, vol. 74, Article ID 102389, 2021.
[39] W. Ahmad, J. A. Hernandez, S. Saini, and R. K. Mishra, "The US equity sectors, implied volatilities, and COVID-19: what does the spillover analysis reveal?" *Resources Policy*, vol. 72, Article ID 102102, 2021.
[40] B. J. Blair, S. H. Poon, and S. J. Taylor, "Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns," in *Handbook of Quantitative Finance and Risk Management*, pp. 1333–1344, Springer, Boston, MA, USA, 2010.
[41] E. Asafo-Adjei, P. Owusu Junior, and A. M. Adam, "Information flow between Global Equities and Cryptocurrencies: a VMD-based entropy evaluating shocks from COVID-19

pandemic," *Complexity*, vol. 2021, Article ID 4753753, 25 pages, 2021.
[42] M. Gallegati, "A wavelet-based approach to test for financial market contagion," *Computational Statistics & Data Analysis*, vol. 56, no. 11, pp. 3491–3497, 2012.
[43] E. Asafo-Adjei, D. Agyapong, S. K. Agyei, S. Frimpong, R. Djimatey, and A. M. Adam, "Economic policy uncertainty and stock returns of Africa: a wavelet coherence analysis," *Discrete Dynamics in Nature and Society*, vol. 2020, Article ID 8846507, 8 pages, 2020.
[44] E. Asafo-Adjei, A. M. Adam, and P. Darkwa, "Can crude oil price returns drive stock returns of oil producing countries in Africa? Evidence from bivariate and multiple wavelet," *Macroeconomics and Finance in Emerging Market Economies*, pp. 1–19, 2021.
[45] A. W. Lo, *The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective*, papers. ssrn. com, 2004.
[46] A. W. Lo, "Reconciling efficient markets with behavioral finance: the adaptive markets hypothesis," *The Journal of Investment Consulting*, vol. 7, no. 2, pp. 21–44, 2005.
[47] M. Lekhal and A. El Oubani, "Does the Adaptive Market Hypothesis explain the evolution of emerging markets efficiency? Evidence from the Moroccan financial market," *Heliyon*, vol. 6, no. 7, Article ID e04429, 2020.
[48] P. Ferreira, A. Dionísio, and S. M. S. Movahed, "Assessment of 48 stock markets using adaptive multifractal approach," *Physica A: Statistical Mechanics and Its Applications*, vol. 486, pp. 730–750, 2017.
[49] U. A. Müller, M. M. Dacorogna, R. D. Davé, O. V. Pictet, R. B. Olsen, and J. R. Ward, *Fractals and Intrinsic Time: A challenge to Econometricians*, Olsen & Associates, Zürich, Switzerland, 1993.
[50] E. Asafo-Adjei, S. Frimpong, P. Owusu Junior, A. M. Adam, E. Boateng, and R. Ofori Abosompim, "Multi-frequency information flows between global commodities and uncertainties: evidence from COVID-19 pandemic," *Complexity*, vol. 2022, Article ID 6499876, 32 pages, 2022.
[51] Q. Peng, F. Wen, and X. Gong, "Time-dependent intrinsic correlation analysis of crude oil and the US dollar based on CEEMDAN," *International Journal of Finance & Economics*, vol. 26, no. 1, pp. 834–848, 2021.
[52] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: a noise-assisted data analysis method," *Advances in Adaptive Data Analysis*, vol. 01, no. 01, pp. 1–41, 2009.
[53] M. E. Torres, M. A. Colominas, G. Schlotthauer, and P. Flandrin, "A complete ensemble empirical mode decomposition with adaptive noise," in *Proceedings of the IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pp. 4144–4147, IEEE, Prague, Czech Republic, May, 2011.
[54] H. M. Nazir, I. Hussain, I. Ahmad, M. Faisal, and I. M. Almanjahie, "An improved framework to predict river flow time series data," *PeerJ*, vol. 7, Article ID e7183, 2019.
[55] P. M. Osei and A. M. Adam, "Quantifying the Information Flow between Ghana Stock Market Index and its Constituents Using Transfer Entropy," *Mathematical Problems in Engineering*, vol. 2020, Article ID 6183421, 10 pages, 2020.
[56] J. Helske, P. Luukko, and M. J. Helske, *Package 'Rlibeemd'*, 2018.
[57] C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, no. 3, pp. 379–423, 1948.
[58] R. V. L. HartleyHartley, "Transmission of Information1," *Bell System technical journal*, vol. 7, no. 3, pp. 535–563, 1928.
[59] S. Behrendt, T. Dimpfl, F. J. Peter, and D. J. Zimmermann, "RTransferEntropy - quantifying information flow between different time series using effective transfer entropy," *Software*, vol. 10, Article ID 100265, 2019.
[60] S. Kullback and R. A. Leibler, "On information and sufficiency," *The Annals of Mathematical Statistics*, vol. 22, no. 1, pp. 79–86, 1951.
[61] A. Renyi, "On the number of endpoints of a k-tree," *Studia Scientiarum Mathematicarum Hungarica*, vol. 5, pp. 5–10, 1970.
[62] A. M. Adam, "Susceptibility of stock market returns to international economic policy: evidence from effective transfer entropy of Africa with the implication for open innovation," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 6, no. 3, p. 71, 2020.
[63] C. Beck and F. Schögl, *Thermodynamics of Chaotic Systems*, Cambridge University Press, Cambridge UK, 1995.
[64] R. Marschinski and H. Kantz, "Analysing the information flow between financial time series," *The European Physical Journal B*, vol. 30, no. 2, pp. 275–281, 2002.
[65] T. Dimpfl and F. J. Peter, "Using transfer entropy to measure information flows between financial markets," *Studies in Nonlinear Dynamics and Econometrics*, vol. 17, no. 1, pp. 85–102, 2013.
[66] A. M. Adam, K. Kyei, S. Moyo, R. Gill, and E. N. Gyamfi, "Multifrequency network for SADC exchange rate markets using EEMD-based DCCA," *Journal of Economics and Finance*, vol. 46, no. 1, pp. 145–166, 2021.
[67] J. H. Chen and Y. F. Huang, "Long memory and structural breaks in modelling the volatility dynamics of VIX-ETFs," *International Journal of Business, Economics and Law*, vol. 4, no. 1, pp. 54–63, 2014.
[68] M. Balcilar and R. Demirer, "Effect of global shocks and volatility on herd behavior in an emerging market: evidence from Borsa Istanbul," *Emerging Markets Finance and Trade*, vol. 51, no. 1, pp. 140–159, 2015.
[69] A. F. Del Castillo Olivares, A. Kumiega, G. Sterijevski, and B. Van Vliet, "An empirical study of volatility spillover worldwide," *Wilmott*, vol. 2018, no. 95, pp. 48–59, 2018.
[70] M. Neffelli and M. R. Resta, "Is VIX still the investor fear gauge? Evidence for the US and BRIC markets," 2018, https://arxiv.org/abs/1806.07556.
[71] S. Akdağ, İ. Kiliç, and H. Yildirim, "Does VIX scare stocks of tourism companies?" *Letters in Spatial and Resource Sciences*, vol. 12, no. 3, pp. 215–232, 2019.
[72] I. Shaikh and A. K. Tripathy, "The Investor Fear Gauge Index (VIX): A Case of Asia-pacific Securities Market," *The Empirical Economics Letters*, vol. 16, no. 6, 2017.
[73] R. Bhuyan, M. G. Robbani, B. Talukdar, and A. Jain, "Information transmission and dynamics of stock price movements: an empirical analysis of BRICS and US stock markets," *International Review of Economics & Finance*, vol. 46, pp. 180–195, 2016.
[74] A. Dutta, "Implied volatility linkages between the U.S. and emerging equity markets: a note," *Global Finance Journal*, vol. 35, pp. 138–146, 2018.
[75] E. Bouri, D. Lien, D. Roubaud, and S. J. Hussain Shahzad, "Fear linkages between the US and BRICS stock markets: a frequency-domain causality," *International Journal of the Economics of Business*, vol. 25, no. 3, pp. 441–454, 2018.
[76] M. Cheuathonghua, C. Padungsaksawasdi, P. Boonchoo, and J. Tongurai, "Extreme spillovers of VIX fear index to international equity markets," *Financial Markets and Portfolio Management*, vol. 33, no. 1, pp. 1–38, 2019.

[77] O. M. Al Nasser and M. Hajilee, "Integration of emerging stock markets with global stock markets," *Research in International Business and Finance*, vol. 36, pp. 1–12, 2016.
[78] A. Todea, "Cross-correlations between volatility, volatility persistence and stock market integration: the case of emergent stock markets," *Chaos, Solitons & Fractals*, vol. 87, pp. 208–215, 2016.
[79] Z. Zhongxiu and L. Qingxin, "Promoting BRICS cooperation for economic growth and development," *Revista Tempo do Mundo*, no. 22, pp. 39–57, 2020.
[80] S. Claessens and K. Forbes, "International financial contagion: an overview of the issues and the book," *International financial contagion*, pp. 3–17, 2001.
[81] R. Glick and A. K. Rose, "Contagion and trade," *Journal of International Money and Finance*, vol. 18, no. 4, pp. 603–617, 1999.
[82] F. Caramazza, L. A. Ricci, and R. Salgado, *Trade and Financial Contagion in Currency Crises*, 2000.
[83] W. Mohti, A. Dionísio, I. Vieira, and P. Ferreira, "Financial contagion analysis in Frontier markets: evidence from the US subprime and the Eurozone debt crises," *Physica A: Statistical Mechanics and Its Applications*, vol. 525, pp. 1388–1398, 2019.
[84] J. Baruník and T. Křehlík, "Measuring the frequency dynamics of financial connectedness and systemic risk∗," *Journal of Financial Econometrics*, vol. 16, no. 2, pp. 271–296, 2018.
[85] S. K. Agyei, A. M. Adam, A. Bossman et al., "Does volatility in cryptocurrencies drive the interconnectedness between the cryptocurrencies market? Insights from wavelets," *Cogent Economics & Finance*, vol. 10, no. 1, Article ID 2061682, 2022.
[86] E. Asafo-Adjei, E. Boateng, Z. Isshaq, A. A. A. Idun, P. Owusu Junior, and A. M. Adam, "Financial sector and economic growth amid external uncertainty shocks: insights into emerging economies," *PLoS One*, vol. 16, no. 11, Article ID e0259303, 2021.
[87] A. Bossman, P. Owusu JuniorOwusu Junior, and A. K. Tiwari, "Dynamic connectedness and spillovers between Islamic and conventional stock markets: time- and frequency-domain approach in COVID-19 era," *Heliyon*, vol. 8, no. 4, Article ID e09215, 2022.
[88] E. Boateng, E. Asafo-Adjei, A. Addison et al., "Interconnectedness among commodities, the real sector of Ghana and external shocks," *Resources Policy*, vol. 75, Article ID 102511, 2022.