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Research Article

A CEEMDAN-Based Entropy Approach Measuring Multiscale Information Flow between Macroeconomic Conditions and Stock Returns of BRICS

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We model a mixture of asymmetric and nonlinear bidirectional and unidirectional causality between four macroeconomic variables (exchange rate, GDP, global economic policy uncertainty, and relative CPI) and stock returns of BRICS economies in the frequency-domain using the information flow theory. The Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN)-based Rényi effective transfer entropy approach is used to establish dynamic flow of information between macroeconomic variables and stock returns of BRICS. The original return series suggested insignificant information flow between most macroeconomic variables and stock returns. However, we reveal both asymmetric and tail dependent analyses at diverse scales between macroeconomic variables and stock returns of BRICS economies. Moreover, we find negative significant flow of information between the variables, in that knowing the history of one variable (either stock or macroeconomic variable), in this case, indicates considerably more uncertainty than knowing the history of only the other variable (either stock or macroeconomic variable). We also observe that global economic policy uncertainty has the most significant adverse causal relationship with stock returns of BRICS, especially in the long term. These results have important implications that investors and policymakers should take into account. Regulators should consider instituting sound policy actions geared towards minimising long-term effects of external shocks and uncertainties.

1. Introduction

The nexus between stock returns and macroeconomic variables abounds in empirical literature around the world. However, the impact of crises such as the COVID-19 pandemic influences a lot of economic activities across the globe and draws the attention of several researchers to establish its effect in several dynamics [1–4]. The COVID-19 pandemic influence on the nexus between most financial time series depicts negative outcomes as revealed by prior studies [5–7]. Specifically, it has altered the spending patterns of most households and governments [8] which precipitates to a decline in economic growth [9, 10]. From the foregoing, in addition to other crises such as the 2007–2009 Global Financial Crisis, Eurozone crisis, and Brexit, there is a greater expectation for business cycle fluctuations to meander the patterns of macroeconomic conditions over time [11, 12].

Over several decades, researchers all over the world have gained massive interest in the role macroeconomic variables play in the fluctuations of stock market returns [13]. Also, from a theoretical perspective, the Arbitrage Pricing Theory formulated by Ross [14] to minimise the discrepancy of the capital asset pricing model (CAPM) predicts the relationship between the returns of an asset as a function of several independent factors and has been instrumental in assessing the macroeconomic-stock returns nexus [15]. As the saying goes, "'stock market discounts everything,"' thus the stock market acts as a barometer which reflects whatever events that arise in a given economy [16]. These events may include fluctuations in inflation rate; interest rates; unemployment rate; economic policy uncertainties; natural disasters such as cyclones, floods, draughts, terrorist attacks; and many more.

The stock markets' effect on macroeconomic variables is however less debated than the latter's effect on stock markets. For instance, as there is growth in the level of GDP, corporate earnings increase, which makes it bullish for stocks. As GDP falls, business and consumer spending levels decline, lowering market performance. Nevertheless, the stock market is a sentiment indicator that has the ability to influence macroeconomic variables [17]. Gross domestic product, for example, is a metric that calculates the total output of a country's economy [18]. As the valuation of the stock market fluctuates, so do investor sentiments. Investors' sentiments affect their spending habits. Economic growth is either accelerated or slowed by changes in spending levels. This is therefore determined by the type of stock market whether bearish or bullish markets. It is worth noting that stock prices are dropping in bearish stock markets, and consumers and businesses have less income and confidence, resulting in less investment, which reduces GDP. In the case of bullish stock markets, the opposite is also true. This is supported by both the supply-side approach [19], which hypothesises causality from financial markets to economic growth, and the demand-side approach [20], which proposes that economic growth causes financial market development. Thus, economic expansion has a direct effect on consumer spending, which can contribute to a surge in demand for goods and services [21]. As a result, an increase in demand pushes up prices, resulting in demand-pull inflation. This can be mitigated by adopting a contractionary fiscal and monetary policy, such as cutting government spending and raising taxes, or raising interest rates, which in the long run lowers asset prices due to the equity valuation model [22].

From the equity parity theory as an emerging theory in international finance, it illustrates the connection between equity and currency movements [23–25]. According to this theory, when investors' foreign or international holdings outperform domestic holdings, domestic investments are exposed to higher exchange rates which devalue domestic currencies contributing to inflation [26]. These inflationary pressures are mitigated by higher interest rates which plunge domestic asset values in the long run [27]. Furthermore, to decrease the exchange rate risk, domestic investors may repatriate part of their foreign holdings as a reaction to adverse movements in domestic currency. By doing so, foreign currency is sold contributing to its depreciation. The stock-oriented theory, on the other hand, theorizes a direct link between exchange rates and domestic financial assets [28]. This exists when demand for financial assets, such as stocks, grows (falls) and the exchange rate reacts to demand and supply of domestic financial assets, which is required to diversify a portfolio globally [28, 29]. The flow-oriented theory on the other hand, in brief, provides that the movement in exchange rate is accompanied by a corresponding movement in asset prices [30]. It goes to reason that stock returns and most macroeconomic variables are bidirectional as also revealed by extant literature [31, 32].

However, the complete discussion above cannot suffice if we do not know what drives a country's economic activities. The financial markets in an economy are closely interconnected with those in other economies around the world due to the financial market integration theory [33–35]. This is especially true in emerging markets [35]. As a result, emerging economies have become increasingly important to the global investment community in recent years for a variety of reasons, including expectations of growing dominance in the international arena as well as significant shifts in capital flows into their financial markets markets [35, 36]. Consequently, improvement in the flow of capital and susceptibility of prices and returns to traded financial assets in diverse countries balance towards the advancement of economic activities. This is in line with the postulations of economists in the late 1800s and the 1900s who argued that excluding the role of the financial system in any discourse on economic growth will give a limited and myopic view of the phenomenon [37–39] despite the unflinching criticisms. This can be found in BRICS economies which have demonstrated immense growth and have become more integrated with developed markets in the context of trade and investment [40]. The BRICS countries have gained much attention from domestic and global investors, portfolio managers, and policymakers due to the improvement of their size and volume of investment. The future of BRICS have been touted to be phenomenal; therefore, a study that delves into their financial markets and macroeconomic conditions is imperative.

A plethora of studies have widely researched the role macroeconomic conditions play in stock markets and have warranted diverse methodologies. An interesting paper provided by Adam and Tweneboah [41] assessed the influence of macroeconomic variables on Ghanaian stock market with reference to Johansen's cointegration through the vector error correction model and revealed a long run relationship. Also, Parab and Reddy [42] investigated the dynamics of macroeconomic variables in Indian stock market by employing the Bai–Perron test and found a significant influence which varies across structural periods. In the context of South Africa, Ndlovu et al. [43] examined the linkages between macroeconomic variables and stock prices for the Johannesburg stock exchange by utilising cointegration tests, variance decomposition, and impulse response function. They found that macroeconomic variables contribute to stock price for each methodology used. Furthermore, Chandrashekar et al. [44] examined the impact of macroeconomic variables on stock prices of two emerging countries (Brazil and India) by employing the Johansen-Fisher panel cointegration and found a long run relationship between the variables. Megaravalli and Sampagnaro [45] also investigated the influence of macroeconomic variables on the Asian stock market (India, China, and Japan) by utilising cointegration tests and revealed a long run relationship. In addition, a study by Rehman [40] makes a contribution towards macroeconomic-stock return nexus in the context of BRICS countries through a panel cointegration approach with findings not far from prior literature.

Notwithstanding, recent studies on the macroeconomic-stock price/returns nexus are gaining much interest in time-frequency models to assess their time and frequency dynamics such as wavelet analysis [32, 33, 46–52]. But when using wavelet analysis, a predefined mother wavelet is needed to decompose a signal, and the selection of the mother wavelet is biased [53, 54]. However, empirical mode decomposition (EMD) and its adjustments overcome this problem since it is a data-driven procedure that decomposes time-series into intrinsic mode functions (IMFs) which are interpreted as time-horizons (amplitude-modulated-frequency-modulated signals). Specifically in the context of this study, the IMFs represent short-, medium-, and long-term periods [55]. The decomposition algorithms are analytical and highly adaptive and are specifically designed to deal with nonlinear, nonstationary, and complex data without making assumptions about the time series' properties [54]. Because the EMD approach outperforms wavelet analysis, several researchers use EMD to investigate fluctuations in macroeconomic factors and other variables [56, 57].

A myriad of studies have assessed either the long-run or short-run nexus of macroeconomic variables and stock prices in addition to the time and frequency domain techniques which assume a linear relationship albeit the real interactions between financial time series are nonlinear [1, 34, 58]. Few or no studies described the macroeconomic variables-stock returns nexus through the power of transfer entropy at different time-horizons while eliminating noise from the time series. This is to say, many studies do not use the decomposition based-transfer entropy to quantify the information flow between stocks and macroeconomic variables. The few studies that consider the flow of information between aforesaid variables do not use methods that reduce noise. Categorically, no studies, to the best of our knowledge, have combined both transfer entropy and decomposition techniques to examine the stock and macroeconomic variables nexus.

Transfer entropy, specifically the Rényi transfer entropy, depends on a weighting parameter q. When q is low, the information in the tails is given more weight, ensuring that the effective transfer entropy is significant. This indicates that tail events are very informative [59] and would help to accurately predict movements between macroeconomic variables and stocks. Further, we decompose the data to also illustrate stock market participants' diverse investment time scales, which is in line with the heterogeneous market hypothesis (HMH) as indicated by Müller et al. [60]. More so, the adaptive market hypothesis (AMH) engineered by Lo [61] posits that markets evolve—due to events and structural changes and adapt—and market efficiency varies in degree at different times. In this regard, decomposition techniques reduce noise (weak signals) to maintain the true signals [1, 34, 55]. This will improve the outcome of the study [1, 34, 55] especially when the flow of information between macroeconomic variables and stocks, which are established to experience rapid oscillations [40], is examined.

The study, therefore, applies the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) proposed by Torres et al. [62] to solve the problem of mode mixing caused by the EMD method as well as the inability of the EEMD to completely eliminate Gaussian white noise after signal reconstruction [63]. Mode mixing, according to Wu and Huang [64], is defined as any IMF consisting of oscillations of intensely disparate amplitude, mostly caused by the intermittency of the driving mechanism. Thus, the physical meaning of an IMF can cease by itself, indicating falsely that there may be different physical processes represented in a mode. We decompose the macroeconomic variables and stock returns because these financial time series data undergo seasonal adjustments or experience rapid oscillations.

Furthermore, we consider the transfer entropy which occurs from the formulation of conditional related information [65]. Transfer entropy quantifies the reduction in uncertainty especially when conditioned on past values of forecasting variables and thus makes it easier to model the statistical causality between variables in a natural phenomenon. It provides an asymmetric method to measure the flow of information between stochastic variables. In the context of this study, the flow of information from macroeconomic variables to stock markets depicts how the two variables comove. Quantifying information transfer from dominant macroeconomic variables to stock markets of BRICS economies is of principal interest to market agents. This is demonstrated by the fact that significant shifts in emerging markets as well as financial crises resulting from rapid and unanticipated oscillations in stock markets and macroeconomic factors have become a commonplace in these economies. This realisation makes it essential to investigate the flow of information between these markets and macroeconomic conditions. Transfer entropy has warranted diverse application in several fields of study for with a wider application in finance and economics [1, 34, 58, 66–69].

Hence, the CEEMDAN-based transfer entropy approach acts as an impetus to understanding the mechanism through which information flow between macroeconomic variables and stock returns via a decomposition of time-series into intrinsic mode functions (IMFs) at various intrinsic times. Moreover, by analysing the flow of information between macroeconomic variables and each BRICS' stock returns, it enables us to acquire replies for each country individually rather than the average response acquired using the traditional panel data methods [46].

The multiscale information flow analysis in this way is needed to investigate the predictability of the system over a range of intrinsic times of short-, medium-, and long-terms. Therefore, it is predicated on the idea that complex systems' financial time series, which are linked to a hierarchy of interdependent regulatory mechanisms, typically produce complex oscillations over a number of intrinsic periods of information exchange between stock returns and macroeconomic variables. Accordingly, the multiscale information flow system is able to capture the extent of heterogeneity with which investors respond to market news across intrinsic times with their relentless search for competing risks and rewards which facilitates information flows among stock returns and macroeconomic variables.

Since stock returns are influenced by a number of macroeconomic variables, we ensure a careful selection of these macroeconomic variables to assess their causality with stocks. Accordingly, four macroeconomic variables which have greater influence on economic activities and may be of much concern to domestic and global investors of stocks are utilised. As indicated by prior studies, these are exchange rate [36], gross domestic product [70], global economic policy uncertainty [51], and inflation rate [71].

The paper contributes to the literature in many ways. We employ the CEEMDAN-based transfer entropy to measure the direction and magnitude of information transfer between macroeconomic variables and stock market returns to determine which macroeconomic variable(s) dominate(s) information flow to the stock markets of BRICS economies at diverse time scales. In this way, we can explore the multiscale (short-, medium-, and long-term) information that might be ignored. Due to the nonlinearity of most financial time series, we adopt a log-likelihood ratio transfer entropy which quantifies information from a probability density function to fill a gap in the extant literature on macroeconomic-stock market nexus, which mostly utilises linear models. Despite the popularity of transfer entropy and decomposition techniques in finance and economic literature, there is no study, to the best of our knowledge, which has concentrated on quantifying the flow of information between macroeconomic variables and BRICS' stocks operating in the multiscale perspective using CEEMDAN-based transfer entropy.

In addition to the country specific macroeconomic variables, we consider global economic policy uncertainty, which has stimulated attention from researchers, investors, and policy makers since the 2007–2009 Global Financial Crisis [46, 51, 68]. Thus, economic policy uncertainty, which includes uncertainty related to monetary policy, fiscal policy, or rules and regulations, can adversely distress the financial system. Suffice to say, since economic policy uncertainty shocks have the tendency of impacting international stock returns, we employed the global economic policy uncertainty in addition to other macroeconomic variables to assess their information flow with stock markets of BRICS.

From the foregoing arguments, the following hypothesis is found:

(i) There is a significant causal relationship between stock returns and macroeconomic variables across investment horizons.

We document a negative significant flow of information between the variables; in that, knowing the history of one variable, in this case, indicates more uncertainty considerably than knowing the history of only the other variable. We also observe that global economic policy uncertainty hasthe most significant adverse causal relationship with stock returns of BRICS, especially in the long-term.

The remaining sections are systematised as follows. The next section discusses the issue of research methodology, and Section 3 offers the results and discussion of the study. Section 4 contains the study's conclusion, which includes the findings' implications and suggestions.

2. Methodology

The analysis of the study was performed using both CEEMDAN and transfer entropy techniques. We first present the CEEMDAN method, which is followed by the transfer entropy, specifically, the Rényi transfer entropy.

2.1. CEEMDAN

2.1. CEEMDAN. Empirical mode decomposition techniques have gained rapid attention by researchers due to its purely data-driven algorithm to separate scales which are exclusive of predefined basis functions, disparate to wavelet analysis [54]. Nonetheless, the EMD method resorts to the scale mixing problem. This problem was solved with the ensemble empirical mode decomposition method (EEMD) developed by Wu and Huang [72] to incorporate a randomly generated white noise series to the original signal. Thankfully, Torres et al. [62] developed the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) to solve the residual noise in the reconstructed signals within the EEMD by appending the noise to the residual of prior iteration instead of the original signal [54]. The CEEMDAN, compared to EMD, EEMD, and possibly, CEEMD, irrespective of the number of decompositions and reconstruction error of the signal approaches zero, and the completeness is better. Furthermore, 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 $N(\theta i, 1)$ [73]. This is important because the observed data often describe a set of phenomena which may be of different kinds, i.e., which may include phenomena of different quality [74], and these different qualities presents themselves in quantitative discrepancies in financial time series [55].

The macroeconomic variables and stock returns were decomposed into seven IMFs and a residual. This was implemented with the *libeemd R* package [75].

The application of the algorithm is summarised as follows:

Begin 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 refers 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 calculated as

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

The exclusive first residue can be determined as

$$r_1(t) = s(t) - \overline{IMF_n(t)}. \quad (2)$$

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

$$r_{jn}(t) = r_j(t) + \delta_j E_j(Wn(t)), n = 1, 2, 3, \ldots, N, \quad (3)$$

$$\overline{IMF_{j+1}(t)} = \frac{1}{N}\sum_{n=1}^{N} E_1\left[r_{jn}\right]. \quad (4)$$

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

$$r_j(t) = r_{j-1}(t) - \overline{IMF_j(t)}. \quad (5)$$

We employ the default parameter as provided in the package of Helske and Luukko [75].

2.2. Rényi Transfer Entropy. Before we discuss the Rényi transfer entropy, we present the idea of Shannon entropy as a measure of uncertainty upon which transfer entropy is embedded in information theory [76]. We consider a probability distribution with diverse results of a given experiment p_j. Each symbol's average information is specified as

$$H = \sum_{j=1}^{n} P_j \log_2\left(\frac{1}{P_j}\right)_{\text{bits}}, \quad (6)$$

where n denotes number of diverse symbols with respect to the probabilities P_j.

The concept of Shannon entropy [77] was introduced in 1948 by Shannon [77]. It indicates that for a discrete random variable (J) that has a probability distribution of $(P(j))$, the average number of bits needed to optimally encode independent draws [76] can be presented as

$$H_J = -\sum_{j=1}^{n} P(j)\log_2 P(j). \quad (7)$$

With the notion of Markov processes, Shannon entropy [77] is aligned with the concept of Kullback–Leibler distance [78] in order to measure the information flow between two time series. We present I and J as two discrete random variables with corresponding marginal probabilities of $P(i)$ and $P(j)$ and 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 signifies that the probability to detect 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 reflection in $t+1$, the average bits number required once the ex-ante k values are known can be illustrated as indicated in

$$h_j(k) = -\sum_i P\left(i_{t+1}, i_t^{(k)}\right)\log P\left(i_{t+1}|i_t^{(k)}\right), \quad (8)$$

where $i_t^{(k)} = (i_t, \ldots, i_{t-k+1})$ (analogously for process J). In a bivariate perspective as well as relying on the Kullback–Leibler distance [79], information flow from process J to process I is measured by computing the deviation from the generalized Markov property $P(i_{t+1}|i_t^{(k)}) = P(i_{t+1}|i_t^{(k)}, j_t^{(I)})$. The Shannon transfer entropy can thus be presented as shown in

$$T_{J\longrightarrow I}(k, l) = \sum P\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)\log\frac{P\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}{P\left(i_{t+1}|i_t^{(k)}\right)}, \quad (9)$$

where $T_{J\longrightarrow I}$ calculates the information flow from J to I. Analogously, $T_{I\longrightarrow J}$ as a measure for the information flow from I to J can be derived. The main direction of the information flow can be concluded by calculating the difference between $T_{J\longrightarrow I}$ and $T_{I\longrightarrow J}$.

Based on the Shannon entropy [77] so far discussed, we present the Rényi transfer entropy [59] which is contingent on a weighting parameter q and can be calculated as

$$H_J^q = \frac{1}{1-q}\log\sum_j P^q(j), \quad (10)$$

with $q > 0$. For $q \longrightarrow 1$, Rényi entropy converges to Shannon entropy. For $0 < q < 1$, thus, a low probability events receive more weight, while for $q > 1$, the weights benefit outcomes j with a higher initial probability. As a result, Rényi entropy permits to emphasize diverse distribution areas, depending on parameter q [68, 76].

Applying the escort distribution [80] $\varnothing_q(j) = p^q(j)/\sum_j p^q(j)$ with $q > 0$ to normalize the weighted distributions, Rényi transfer entropy [59] is derived as indicated in

$$RT_{J\longrightarrow I}(k, l) = \frac{1}{1-q}P\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)$$
$$\log\frac{\sum_i \varnothing_q\left(i_t^{(k)}\right)P^q\left(i_{t+1}|i_t^{(k)}\right)}{\sum_{i,j}\varnothing_q\left(i_t^{(k)}, j_t^{(I)}\right)P^q\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}. \quad (11)$$

It is worth noting that the Rényi transfer entropy can have negative values. As a result, knowing the history of J depicts even greater uncertainty than would otherwise be indicated by only knowing only the history of I.

The transfer entropy parameters are biased in small samples [81]. The correction of the bias to calculate the effective transfer entropy is shown in

$$ETE_{J\longrightarrow I}(k, l) = T_{J\longrightarrow I}(k, l) - T_{Jshuffled\longrightarrow I}(k, l), \quad (12)$$

where $T_{Jshuffled\longrightarrow I}(k, l)$ depicts the transfer entropy via a shuffled version of the time series J; that is, selecting values at random from the observed time series J and realigning them to form a new time series, destroying the time series dependencies of J, not forgeting the statistical dependencies between J and I. This enjoins $T_{Jshuffled\longrightarrow I}(k, l)$ with increasing sample size, converges to zero, and any nonzero value of $T_{Jshuffled\longrightarrow I}(k, l)$ is as a result of small sample effects. As a result, repeated shuffling and the average of the shuffled transfer entropy estimates across all replications can be used as a small sample bias estimator. This is subtracted from the Shannon or Rényi transfer entropy estimate to get a bias-corrected effective transfer entropy estimate.

Relying on a Markov block bootstrap, the statistical significance of the transfer entropy estimates as given in equation (12) can be inspected as provided by reference [82]. This preserves the dependencies within the variables J and I but ignores the statistical dependencies between J and I opposing to shuffling. The distribution of the estimates under the null hypothesis of no information movement is then determined by repeated estimation of transfer entropy. The associated $p - value$ is given by $1 - \hat{q}T$, where $\hat{q}T$ signifies the simulated distribution's quantile, which is defined by the transfer entropy estimate [76].

2.3. Data Sources and Description. The study employed monthly stock prices of BRICS countries which are made up of Brazil (Ibovespa Index), Russia (Moscow Exchange Russia Index), India (NIFTY 500 Index), China (Shanghai Stock Exchange Composite Index), and South Africa (JSE/FTSE All Share Index). We further consider the relevant macroeconomic variables—exchange rate (national currency per US dollar), gross domestic product (GDP), global economic policy uncertainty (a trio of terms pertaining to the economy (E), policy (P) and uncertainty (U), and inflation rate (relative consumer price indices). The monthly data span 1999/02 to 2021/02 yields a total of 265 observations after eliminating missing data. Specifically, after merging the data to have equal dates to enhance effective comparison, the sample period was obtained to ensure consistent data availability. The suggested period was chosen to cover the 2008 Global Financial Crisis, US-China trade tension, and the COVID-19 pandemic period. Monthly data were selected over yearly series since financial data experience rapid oscillations. However, daily data were not considered due to the inaccessibility of data for most macroeconomic variables.

The data on stock market indices and macroeconomic variables were obtained from Organization for Economic Corporation and Development (OECD) database, while data on global economic policy uncertainty developed by the Baker, Bloom, and Davis [83] was gleaned from the website https://www.policyuncertainty.com/index.html. The monthly data on GDP are not surprising because from the quarterly release of GDP, the OECD constructed the monthly GDP to gauge its short-term dynamics. The monthly GDP is developed from chained volume estimates of quarterly GDP series in US dollars. Through a linear interpolation, the monthly GDP is obtained to align with the required month of a quarter. The study was based on the returns of monthly stock and macroeconomic variables given as $r_t = \ln P_t - \ln P_{t-1}$, where r_t is the continuously compounded return, and P_t and P_{t-1} are current and previous indices, respectively.

3. Results and Discussion

3.1. Preliminary Analysis. Table 1 exhibits the summary of statistics for the markets and macroeconomic setting during the period under study. The skewness values observed show nonnormality across the board with China's stock and inflation rate exhibiting a skewness close to normality of 0.2403 and −0.2112, respectively. On the other hand, kurtosis values further show leptokurtic behaviour in the values across variables especially gross domestic product. In terms of the stationarity test, the Augmented Dicky-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) are used at levels $I(0)$ and at first difference $I(1)$. The observations from both the ADF and the KPSS reveal that all the data series explicitly fulfil the stationarity requirements at first difference. This is in line with assumptions of various autoregressive studies such as reference [84] which assumes global stationarity. Despite the stationarity of the time series returns, we respond further to latent nonstationarity by employing the CEEMDAN-based effective transfer entropy in the context of the study.

Table 2 provides the stationarity tests of all the IMFs for the BRICS economies with respect to exchange rate (EXC), gross domestic product (GDP), Global Economic Policy Uncertainty (GEPU), and inflation and stock returns. Both the ADF and KPSS are employed to facilitate the stationarity analysis. Generally, we document that most series are stationary in the short- and medium-terms (IMFs 1–5), whereas from IMF 6 through to the residual, we notice more nonstationary series.

3.2. Empirical Results. We present the bidirectional CEEMDAN-based Rényi effective transfer entropy estimates in addition to the 95% confidence bounds between BRICS stocks and macroeconomic variables for various intrinsic mode functions (IMFs). The IMFs indicate the importance of multiscales in financial time series. Thus, the dynamics of stock and macroeconomic conditions do not occur instantaneously but at several investment horizons which necessitate the use of multiscale analysis.

Using a vector autoregressive model and a Granger causality test, similar conclusions could be drawn as the transfer entropy [76]. The key benefit of employing transfer entropy, however, is that it is not restricted to linear relationships. This would imply that awareness of either the macroeconomic condition or the stock might suggest a higher risk coverage for the other variable. This is not to say that there is no information flow. In contrast to a situation of positive Rényi transfer entropy, where knowledge of the other variable reduces the risk of the dependent variable, the information flow simply implies a higher risk of the dependent variable. The knowledge in the tails is assigned a high weight for low values of q, resulting in a significant effective transfer entropy result in the current situation. This shows that there is still tail dependence between the stock and the macroeconomic variable. The effective transfer entropy decreases and even becomes negative as the weight is reduced.

The Rényian transfer entropy (RTE) is generally not positive semidefinite [85]. This is due to the fact that Rényi effective transfer entropy emphasises various sections of the involved probability density functions in a nonlinear way. The Rényian transfer entropy is specifically used in this study to account for tail events associated with pricing relevant financial information. When q is low, the information in the

Table 1: Summary statistics.

Statistic	Exchange	Inflation	GEPU	GDP	Stock
Brazil					
Mean	0.0048	−0.0011	0.0030	0.0001	0.0107
Variance	0.0018	0.0015	0.0332	0.0000	0.0047
Skewness	1.1320	−0.9215	0.6593	−3.6081	−0.6879
Kurtosis	4.6714	4.3893	1.6423	62.9347	3.0200
Normtest W*	0.9386	0.9471	0.9709	0.5425	0.9639
ADF at $I(0)$	−1.4043	−1.9999	−2.6666	−3.5697**	−2.1962
ADF at $I(1)$	−6.3711**	−6.8460**	−8.0698**	−6.0008**	−5.8700**
KPSS at $I(0)$	2.2885**	0.6912**	2.8536**	0.5927**	4.1424**
KPSS at $I(1)$	0.1585	0.1641	0.0375	0.0576	0.1440
Russia					
Mean	0.0045	0.0019	0.0030	0.0001	0.0163
Variance	0.0012	0.0009	0.0332	0.0000	0.0067
Skewness	1.3403	−1.1615	0.6593	−3.3684	−0.4165
Kurtosis	6.3440	6.6340	1.6423	62.1799	7.0808
Norm test W*	0.8535	0.8786	0.9709	0.5346	0.9131
ADF at $I(0)$	−1.8123	−2.0458	−2.6666	−4.6812**	−2.1365
ADF at $I(1)$	−6.5762**	−7.1506**	−8.0698**	−4.4573**	−6.1255**
KPSS at $I(0)$	3.5390**	1.8379**	2.8536**	0.0646	4.1893**
KPSS at $I(1)$	0.1209	0.5211	0.0375	0.0445	0.3920
India					
Mean	0.0020	0.0009	0.0030	0.0000	0.0103
Variance	0.0003	0.0002	0.0332	0.0006	0.0034
Skewness	0.7531	−0.3347	0.6593	−4.1368	−0.8751
Kurtosis	2.4870	0.7179	1.6423	93.7683	3.2108
Norm test W*	0.9348	0.9871	0.9709	0.1897	0.9474
ADF at $I(0)$	−1.8441	−3.7848**	-2.6666	−3.8888**	−1.9162
ADF at $I(1)$	−5.3846**	−5.7346**	−8.0698**	−8.4022**	−5.7501**
KPSS at $I(0)$	3.9202**	4.1553**	2.8536**	0.4471*	4.5132**
KPSS at $I(1)$	0.1194	0.0265	0.0375	0.0163	0.0456
China					
Mean	−0.0009	0.0013	0.0030	0.0001	0.0041
Variance	0.0001	0.0002	0.0332	0.0001	0.0040
Skewness	1.0678	−0.2112	0.6593	−6.5488	0.2403
Kurtosis	6.6905	−0.3816	1.6423	119.7692	1.5963
Norm test W*	0.8096	0.9908	0.9709	0.2825	0.9755
ADF at $I(0)$	−1.2312	−2.1965	−2.6666	−4.1416**	−3.9834**
ADF at $I(1)$	−5.2484**	−6.8436**	−8.0698**	−5.9120**	−4.9528**
KPSS at $I(0)$	3.5896**	3.9022**	2.8536**	0.14022	1.8186**
KPSS at $I(1)$	0.1717	0.0900	0.0375	0.0246	0.0460
South Africa					
Mean	0.0035	−0.0011	0.0030	0.0001	0.0089
Variance	0.0015	0.0011	0.0332	0.0000	0.0017
Skewness	0.5749	−0.9183	0.6593	−3.5978	−1.3575
Kurtosis	3.3840	2.9476	1.6423	46.6991	4.9777
Norm test W*	0.9585	0.9566	0.9709	0.5207	0.9231
ADF at $I(0)$	−1.9594	−2.4157	−2.6666	−2.9854	−2.7979
ADF at $I(1)$	−6.0605**	−6.4527**	−8.0698**	−5.1363**	−5.4856**
KPSS at $I(0)$	3.1822**	1.9261**	2.8536**	0.1351	4.4369**
KPSS at $I(1)$	0.0639	0.0341	0.0375	0.0594	0.1327

Note. Norm test W* indicates a non-normal distribution at all conventional levels of significance. *, **, and *** indicate significance at 10%, 5% and 1% levels, respectively.

tails is given more weight, ensuring that the effective transfer entropy is significant [1, 34]. This indicates that tail events are very informative and help to predict movements between macroeconomic variables and stocks. For this reason, we set q from the Rényi effective transfer entropy to 0.3 to usher more weights to tail events such as spikes, which bear direct implications. As indicated by Owusu Junior et al. [1] and Asafo-Adjei et al. [34], setting q to 0.3 offers heavy tails in the returns to reveal the stylized facts of most financial time series. We do this to illustrate that despite the advancements

Table 2: Stationarity tests of IMFs.

	Unit root	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6	IMF 7	Residual
Brazil									
Exchange	ADF	−13.58**	−15.65**	−8.74**	−8.50**	−5.21**	−2.09**	N/A	N/A
	KPSS	0.16**	0.08	0.01	0.02	0.03	0.07	0.26**	0.53**
GDP	ADF	−8.65**	8.52	−6.49**	−8.42**	−3.32*	−0.07	N/A	N/A
	KPSS	0.11	0.10	0.09	0.03	0.03	0.10	0.17**	0.52**
GEPU	ADF	−14.15**	−9.76**	−7.55**	−6.85**	−2.18	1.69	N/A	N/A
	KPSS	0.05	0.10	0.05	0.01	0.04	0.07	0.14*	0.33**
Inflation	ADF	−14.01**	−15.87**	−10.64**	−6.52**	−4.46**	−0.69	N/A	N/A
	KPSS	0.12	0.06	0.02	0.07	0.04	0.07	0.22**	0.52**
Stock	ADF	−15.01**	−13.92**	−5.49**	−7.37**	−4.37**	−3.76**	N/A	N/A
	KPSS	0.07	0.07	0.08	0.05	0.04	0.09	0.19**	0.48**
Russia									
Exchange	ADF	−11.81**	−9.94**	−6.66**	−6.41**	−4.47**	−2.80	N/A	N/A
	KPSS	0.16**	0.14*	0.05	0.07	0.03	0.14*	0.24**	0.53**
GDP	ADF	−5.62**	−10.63**	−9.15**	−6.97**	−3.28*	−3.06	N/A	N/A
	KPSS	0.02	0.07	0.02	0.05	0.03	0.05	0.16**	0.49**
GEPU	ADF	−14.15**	−9.76**	−7.55**	−6.85**	−2.18	1.69	N/A	N/A
	KPSS	0.05	0.10	0.05	0.01	0.04	0.07	0.14*	0.33**
Inflation	ADF	−13.61**	−10.90**	−12.14**	−6.78**	−5.39**	−3.34*	N/A	N/A
	KPSS	0.10	0.13*	0.05	0.02	0.02	0.06	0.27**	0.44**
Stock	ADF	−18.49**	−16.30**	−12.02**	−6.79**	−4.96**	−2.47	N/A	N/A
	KPSS	0.04	0.09	0.04	0.02	0.02	0.21**	0.38**	0.53**
India									
Exchange	ADF	−18.48**	−12.81**	−10.86**	−6.86**	−4.50**	−5.09**	N/A	N/A
	KPSS	0.10	0.07	0.09	0.04	0.02	0.04	0.37**	0.53**
GDP	ADF	−8.65**	8.52	−6.49**	−8.42**	−3.32*	−0.07	N/A	N/A
	KPSS	0.11	0.10	0.09	0.03	0.03	0.10	0.17**	0.52**
GEPU	ADF	−14.15**	−9.76**	−7.55**	−6.85**	−2.18	1.69	N/A	N/A
	0.05	0.10	0.05	0.01	0.04	0.07	0.14	0.33*	0.05**
Inflation	ADF	−13.91**	−11.83**	−10.04**	−5.69**	−1.76	−3.38*	N/A	N/A
	KPSS	0.06	0.06	0.03	0.06	0.02	0.04	0.11	0.50**
Stock	ADF	−19.47**	−11.14**	−10.27**	−5.62**	−4.33**	−3.93**	N/A	N/A
	KPSS	0.06	0.07	0.06	0.03	0.04	0.15*	0.19**	0.47**
China									
Exchange	ADF	−13.58**	−15.65**	−8.74**	−8.50**	−5.21**	−2.09	N/A	N/A
	KPSS	0.16**	0.08	0.01	0.02	0.03	0.07	0.26**	0.53**
GDP	ADF	−8.65**	8.52	−6.49**	−8.42**	−3.32*	−0.07	N/A	N/A
	KPSS	0.11	0.10	0.09	0.03	0.03	0.10	0.17**	0.52**
GEPU	ADF	−14.15**	−9.76**	−7.55**	−6.85**	−2.18	1.69	N/A	N/A
	KPSS	0.05	0.10	0.05	0.01	0.04	0.07	0.14*	0.33**
Inflation	ADF	−15.87**	−10.63**	−12.41**	−8.84**	−5.12**	−3.61**	N/A	N/A
	KPSS	0.07	0.09	0.04	0.01	0.04	0.09	0.24**	0.53**
Stock	ADF	−15.78**	−10.34**	−11.64**	−7.27**	−4.67**	−4.09**	N/A	N/A
	KPSS	0.07	0.13*	0.08	0.01	0.02	0.08	0.10	0.26**
South Africa									
Exchange	ADF	−15.18**	−10.48**	−10.88**	−8.54**	−3.76**	−1.73	N/A	N/A
	KPSS	0.03	0.19**	0.08	0.01	0.04	0.09	0.30**	0.52**
GDP	ADF	−9.95**	8.34	−6.92**	−8.58**	−2.20	−2.76	N/A	N/A
	KPSS	0.11	0.20**	0.12	0.02	0.07	0.06	0.13*	0.52..
GEPU	ADF	−14.15**	−9.76**	−7.55**	−6.85**	−2.18	1.69	N/A	N/A
	KPSS	0.05	0.10	0.05	0.01	0.04	0.07	0.14*	0.33**
Inflation	ADF	−14.73**	−10.66**	−9.69**	−6.50**	−4.35**	−2.77	N/A	N/A
	KPSS	0.04	0.13*	0.07	0.02	0.04	0.08	0.28**	0.47**
Stock	ADF	−18.79**	−15.86**	−9.40**	−6.12**	−5.07**	−2.25	N/A	N/A
	KPSS	0.05	0.07	0.07	0.03	0.04	0.23**	0.20**	0.54**

Note. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

in BRICS economies in terms of trade and investment over the years, their stock returns depict large drawdowns than upward movements to support the stylised facts of most asset returns [35]. Since transfer entropy is a nonparametric estimate and has a higher likelihood of determining statistical dependence between time series, we present the discussion between BRICS stocks and macroeconomic variables following the arbitrage pricing theory in addition to the degree to which investment in stocks may drive the economy as a whole.

Analyses of the study are presented for five economies belonging to BRICS concerning macroeconomic conditions that are apparent to trade and investments and stock returns. The original returns series (without decomposition) are presented in addition to the seven (7) multiscales (IMFs) plus one residual provided by the CEEMDAN and estimated using the RTE. Thus, the final outputs are tail dependent and reveals the directional flow of information between the variables other than the ones shown by other statistical techniques which assumes linearity and stationarity, thereby ignoring tail information. This special phenomenon of the RTE makes it apparent to contribute this study to the prior literature. The eight scales are interpreted in Table 3 referring to the extant literature [54].

Table 3: Notes on IMFs.

IMFs	Meaning
IMFs 1–3	Short term
IMFs 4–7	Medium term
Residual	Long-term trend (fundamental feature)

Figure 1 shows the information transmission between macroeconomic variables and stock market returns of Brazil. The original returns series, without decomposition depicts no significant flow of information between the variables. Although, there are potentials for positive flows from macroeconomic variables to the stock returns and vice versa from the stock returns. These observations imply that the macroeconomic environment and Brazil Ibovespa Index are less active to respond to information flow for the original series. However, the outcome is not startling since the COVID-19 pandemic shock on the economy of Brazil is high, including its recovery from the 2014–2016 recession [86]. Retrospectively, Brazil was considered as one of the fastest growing economies from 2000–2012 with an average annual GDP of over 5%. These rapid oscillations in the economy of Brazil over the years have contributed to the insignificant flow of information throughout the original series. As a result, the different qualities (fluctuations in the economy) [74] present themselves in the quantitative discrepancies in stocks and macroeconomic variables, which may be accurately captured by the diverse scales of decompositions [55].

The decomposed return series illustrate some significant information transmission between the variables. That is, different investment horizons play a significant role in explaining the complex dynamics of the Brazilian economic environment. In the short-term, there is a significant flow of information from the stock returns to the macroeconomic variables but at varying sparsity of the IMFs (IMF1-IMF3). Specifically, from Figure 1, significant information flow from the stock returns to GDP and exchange rate at IMF1 to exchange rate at IMF2 and to all the macroeconomic variables except exchange rate at IMF3, representing the short-term. In the medium-term, significant information flows from the stock to GDP and inflation (at IMF 4), GEPU and GDP (at IMF 6), and GEPU (at IMF 7). However, in the long-term, we notice a significant negative flow of information from the Brazilian stock to all the macroeconomic variables.

The stock market is a sentiment indicator that has the ability to influence macroeconomic variables. As the valuation of the stock market fluctuates, so do investor sentiments. Investors' sentiments affect their spending habits. Economic growth is accelerated by changes in spending levels. The type of market in the short-term suggests a bullish stock-market, and consumers and businesses have more income and confidence, resulting in more investment, which upsurges GDP. In other words, stock market development augments economic growth by attracting more investments [87].

Flows towards stock returns are not immediate in the short term. However, as households invest in foreign equities, the less favourable the domestic currency movements, which reflected the negative significant information flow from the exchange to the stock in the medium term (IMFs 4 and 6). In addition, other scales depict potential negative flows from the exchange rate to the stock thereby heightening uncertainties within the stock market. The depreciation of currency movements leads to inflationary pressures which adversely influence stock returns, thereby rendering an inverse causal relationship between GDP and stock, which is apparent from IMF 2. The dynamics continue until the flow of information exposes a higher risk to the stock returns in IMF 3. The negative influence of GEPU now becomes apparent because the interdependence of trade and financial globalization increases vulnerability of emerging markets to the shocks emanating from the world's leading economy [88]. Inflation, in addition, transmits significant negative information to stock returns at IMFs 2, 3, and 6. At this stage, an effective contractionary monetary policy to increase interest rates may minimise the rate of inflation in the economy. Notwithstanding, the adverse influences of global economic policy uncertainties are not easily controlled, and it is long-lived throughout the remaining scales.

Figure 2 shows the information transmission between macroeconomic variables and stock market returns of Russia. The original returns series without decomposition depicts no significant flow of information except from exchange rate to stocks and from stocks to GDP observed at the tail. Economic growth is declined by adverse changes in spending levels. On the average, the type of market may demonstrate a bearish stock market, and consumers and businesses have less income and confidence, resulting in less investment, which plummets GDP. Throughout the scales, there seem to be less information flows between macroeconomic variables and stocks except for some few cases. For

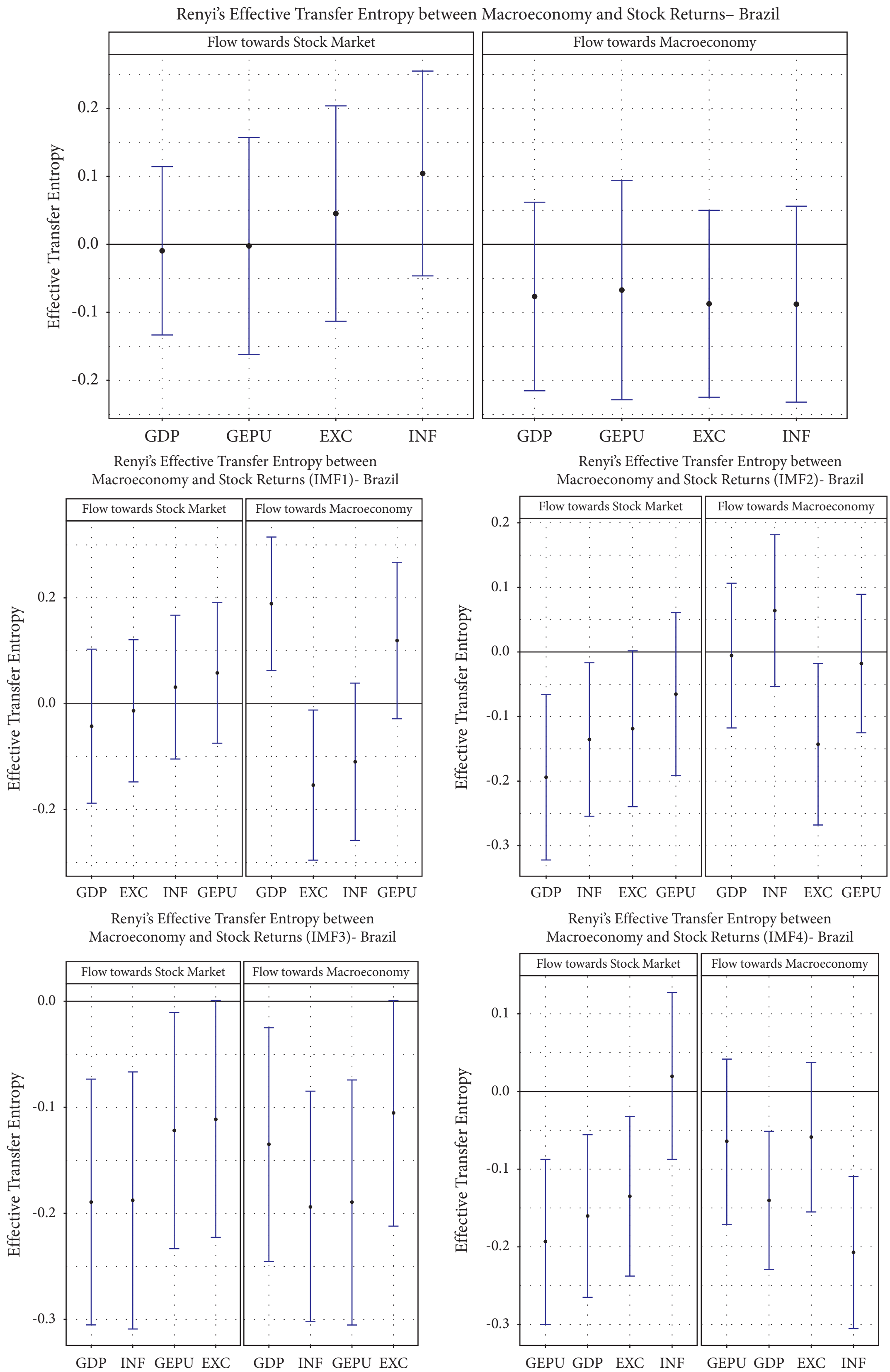

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Figure 1: Continued.

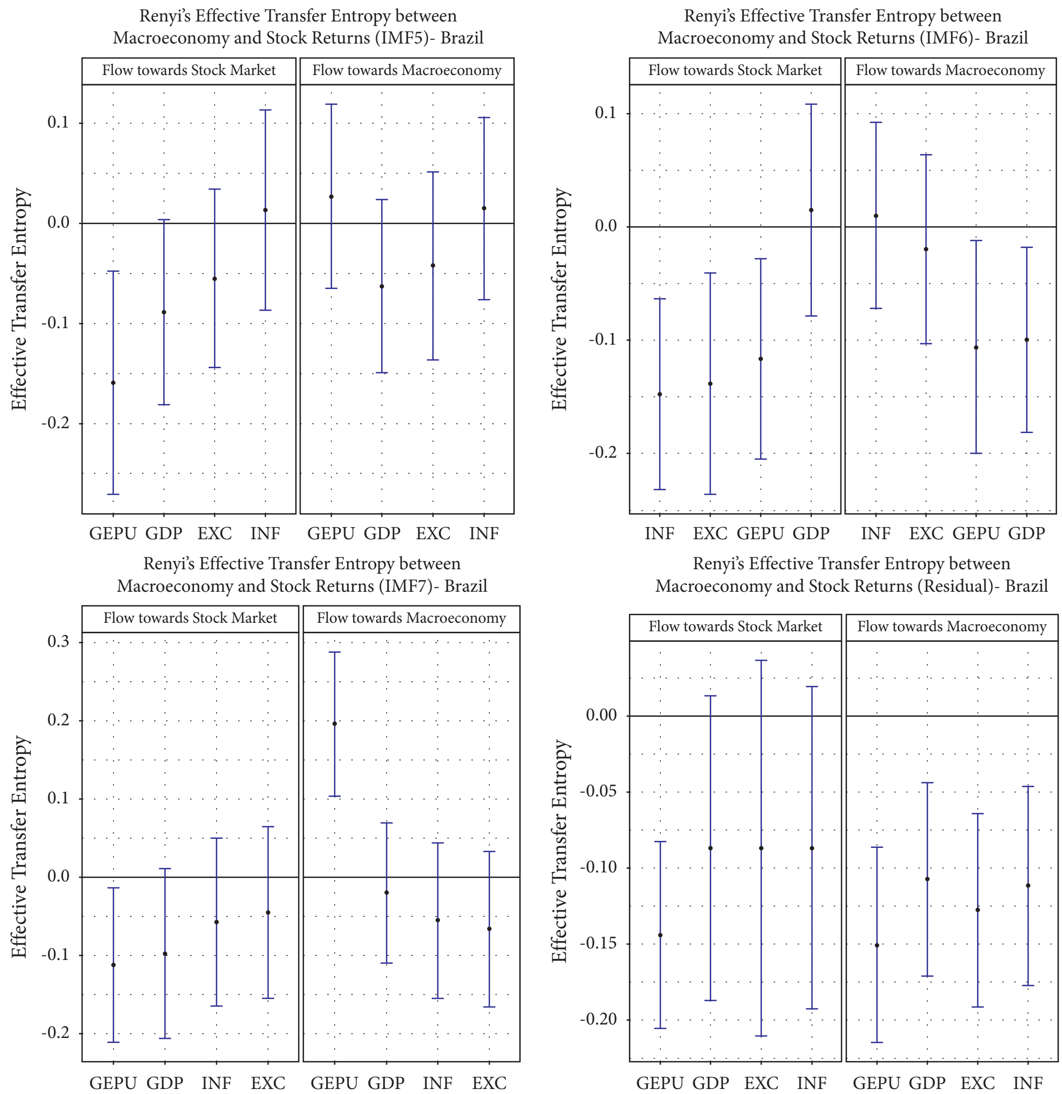

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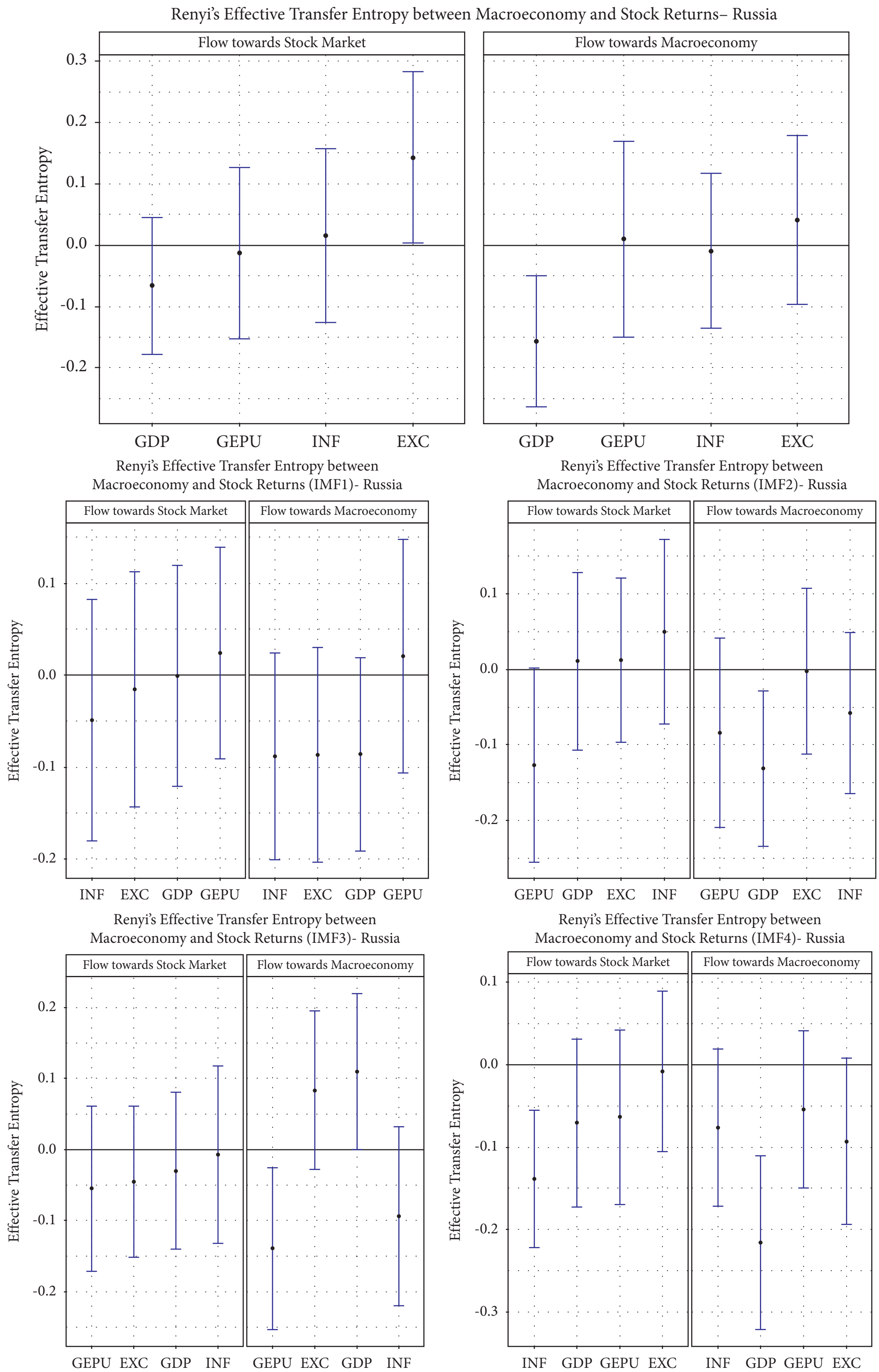
Figure 1: Decomposed macroeconomic factors and stock of Brazil.

instance, in the medium-term, significant negative information flows from inflation to the stock (at IMF4) whereas in the long-run, the adverse impact of GEPU and inflation are felt by stock returns. Thus, knowing the history of stock market returns of Russia depicts even greater uncertainty than would otherwise be indicated by only knowing the history of GEPU and inflation alone. Knowledge of GEPU and inflation suggests higher risk exposure for stock market returns.

Consequently, we notice significant negative flow of information from the stock of Russia to GDP (at IMF 2), GEPU (at IMF 3), and GDP (at IMFs 4 and 5). Generally, we notice a more negative flow of information between macroeconomic variables and stock returns at low probability events.

Figure 3 shows the information transmission between macroeconomic variables and stock market returns of India. The original returns series without decomposition depicts no significant flow of information albeit at the tails. There is an immediate adverse flow of information from inflation and GDP to stock market returns in the short run. Thus, the knowledge of inflation and GDP suggests higher risk exposure for stock market returns of India. However, in the short-term (IMF 2), the knowledge of the inflation reduces the risk of stock returns in India. In other words, the nature of inflation is such that it contributes to the performance of stocks. This is possible when there is an increase in deflation (opposite of inflation) which is evident in the economy of India across time. At IMF 3, we account for most bidirectional information flow between the variables, but negative.



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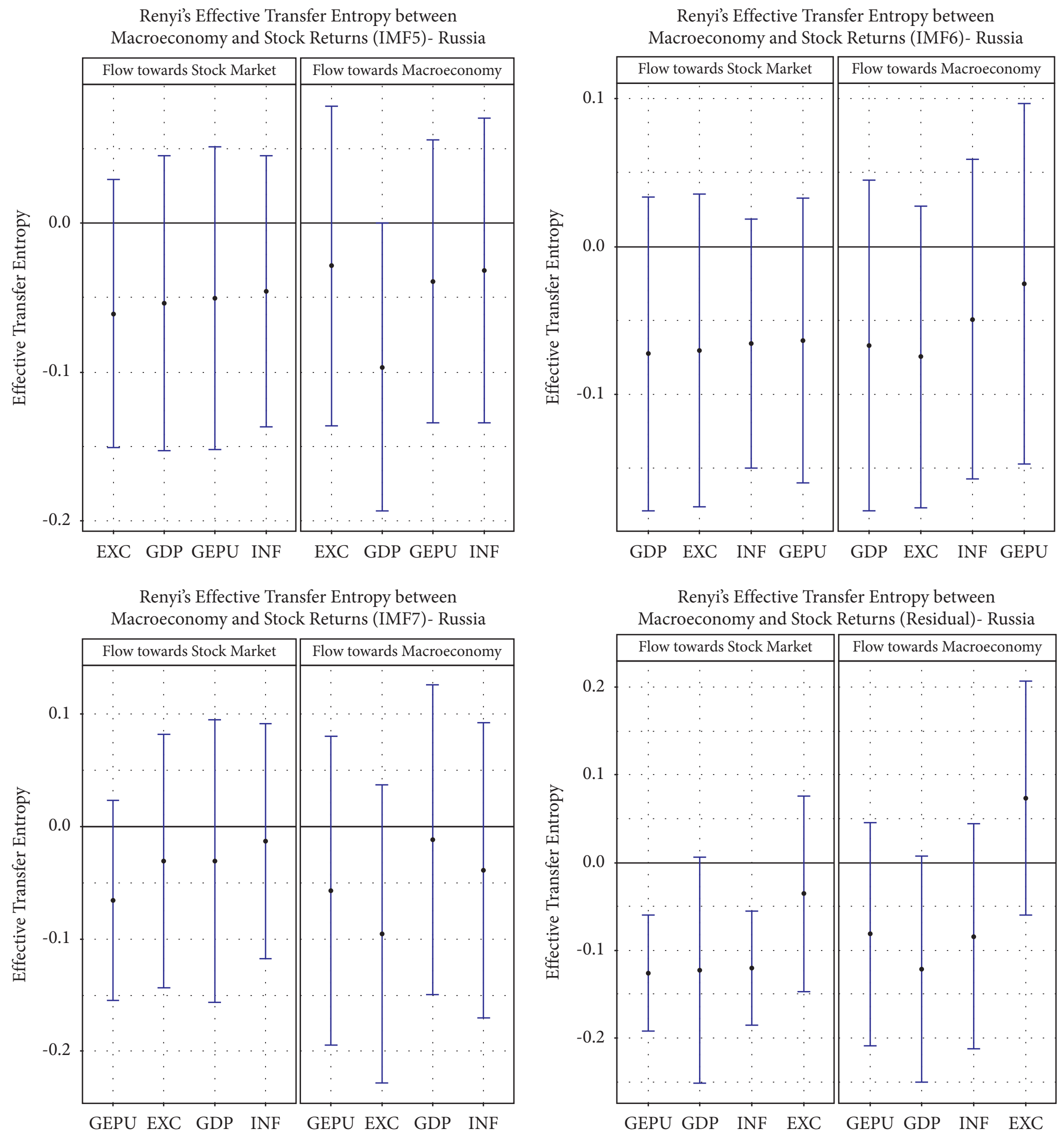
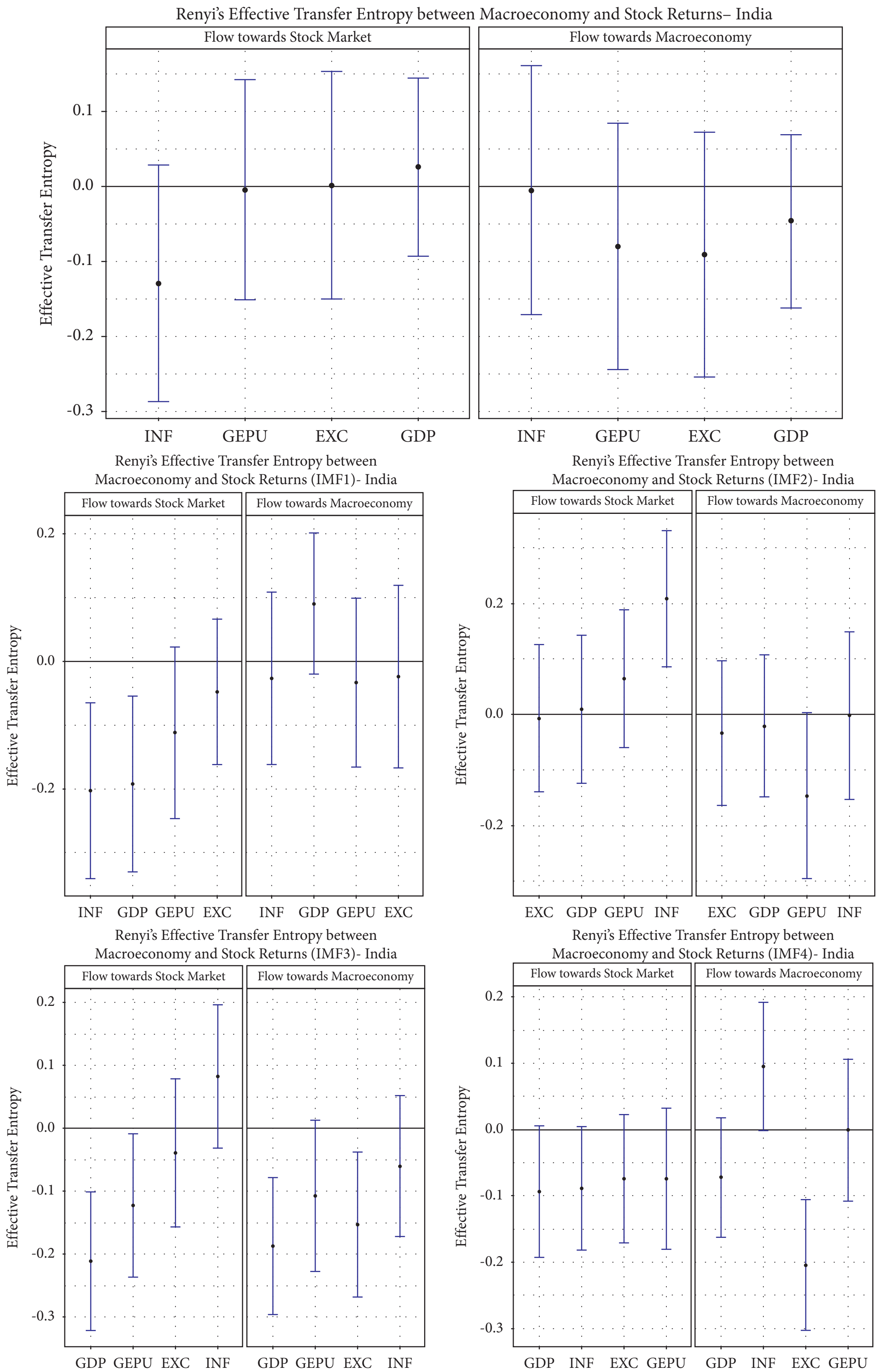


(b)

Figure 2: Decomposed macroeconomic factors and stock of Russia.

In the medium-term, significant negative information flows from stock to exchange rate (at IMFs 4 and 6), and inflation and GDP (at IMF 5). Thus, the observance of one variable imposes a higher risk to the other from surging. This is also evident from the long-term where almost all variables depicted significant negative information flow. Generally, there are more negative flows than positive flows throughout the multiscale at the tails between the variables.

Figure 4 shows the information transmission between macroeconomic variables and stock market returns of China. The original returns series without decomposition depicts no significant flow of information except inflation, which establishes a bicausality relationship with stock. There are positive flows between original stock returns of China and inflation at the low probability event. There is no immediate flow of information between the variables in the short run (at IMF 1). At IMF 2, the knowledge of stock reduces the risk of exchange rate to fall. In other words, a rise in stock prices contribute to a rise in exchange rate (national currency/USD). This may happen when over performance of Chinese stock attracts foreign investments, which contributes positively to domestic currency movements. At IMF 3, exchange rates adversely impact on stock returns of China, which could be due to foreign investments. This signifies that knowledge of the exchange rate exposes Chinese stock to higher risk. Consequently, in the medium-term, stock of China transmits negative information to GDP (at IMFs 4 and 5). It can be observed from the long-run that stock returns of China contribute to a negative impact on macroeconomic variables. That is, a rise in the performance of



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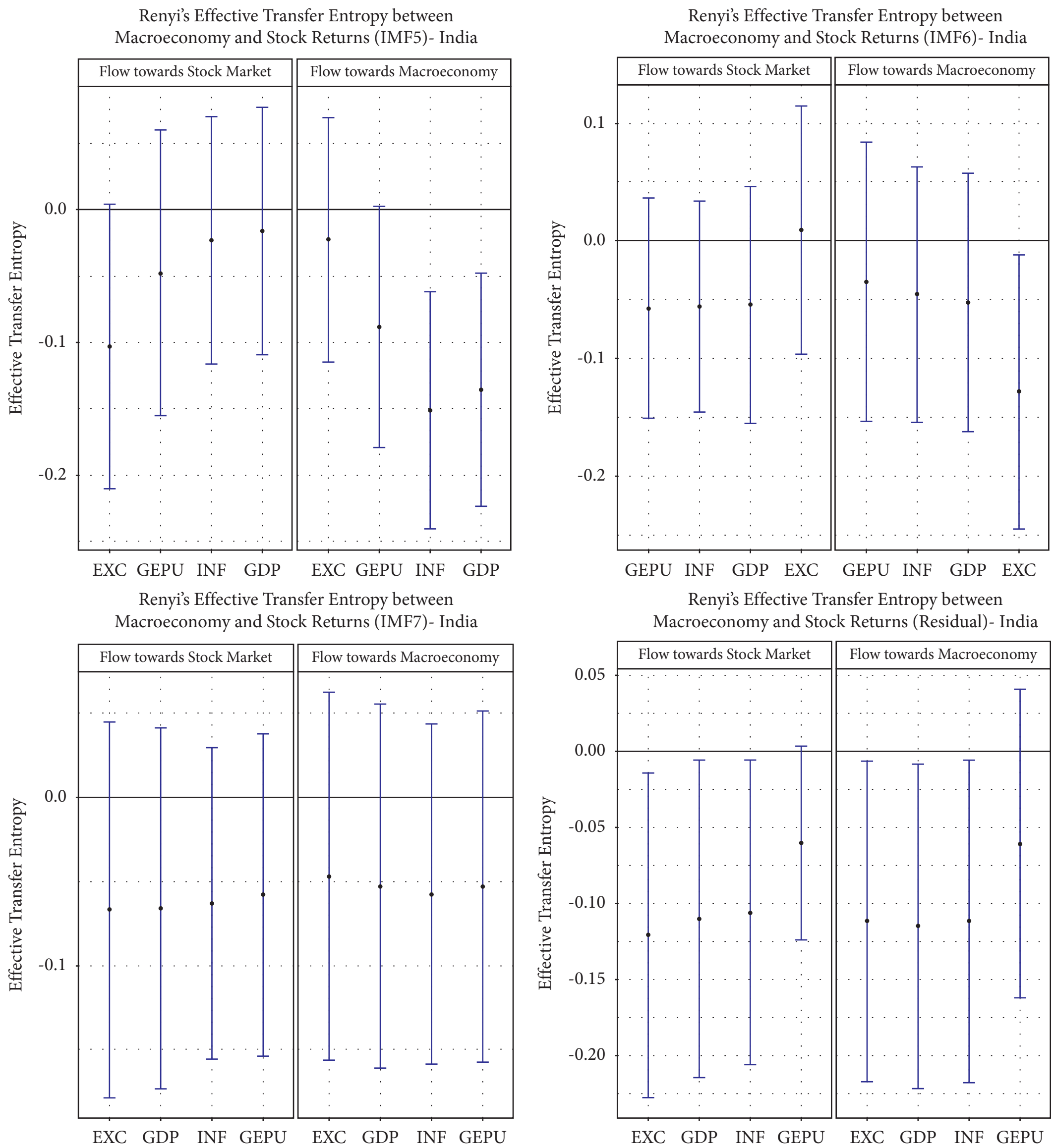

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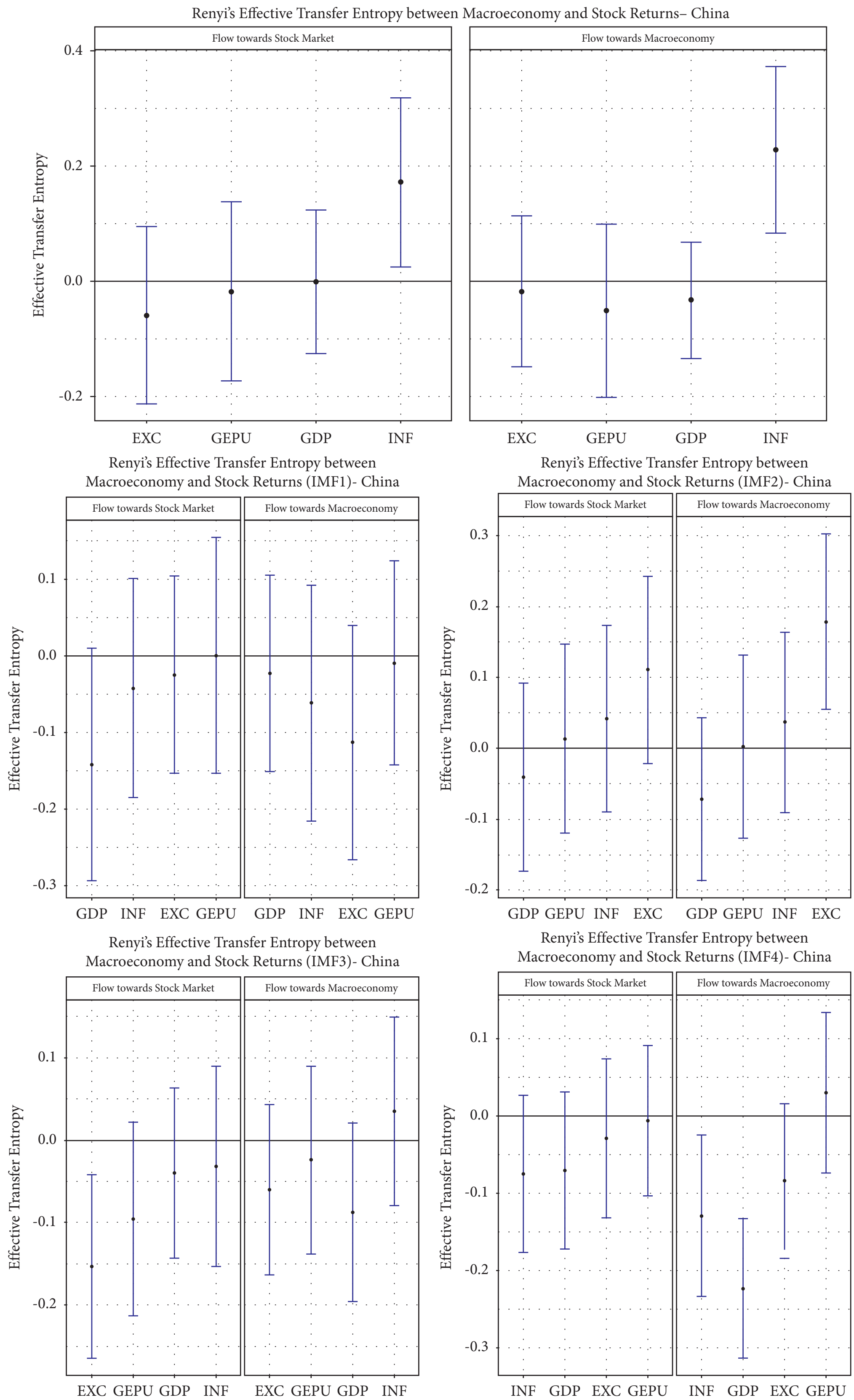
Figure 3: Decomposed macroeconomic factors and stock of India.

stocks contributes to a low impact of macroeconomic conditions. At this point, investors with long-term holdings on the stock of China receive less shocks from country-specific macroeconomic variables. On the other hand, adverse information flows from GEPU to stock returns of China.

Figure 5 shows the information transmission between macroeconomic variables and stock market returns of South Africa. The original returns series without decomposition depicts no significant flow of information except flow from stock to inflation. This establishes a negative flow of information from the performance of stocks to minimise the rate of inflation in the economy at lower probability events. At IMF 1, knowledge of South African stocks exposes less risk to the improvement in gross domestic product. This case is not so at IMF 2 and 4, where knowledge of GDP exposes the stock market of South Africa to higher risk. In other words, a rise in GDP decreases corporate earnings, which makes it bearish for stocks. Furthermore, at IMFs 4, exchange rates adversely impact on stock returns of South Africa, which could be due to foreign investments which result in adverse currency movements. The dynamics of exchange rate movements for South Africa strongly confirms the assertion made by Adam et al. [89] that exchange rate markets are driven by economic fundamentals when the Southern African Development Community was examined using the EEMD technique. Consequently, there is a negative feedback effect from the stock to exchange rate as well



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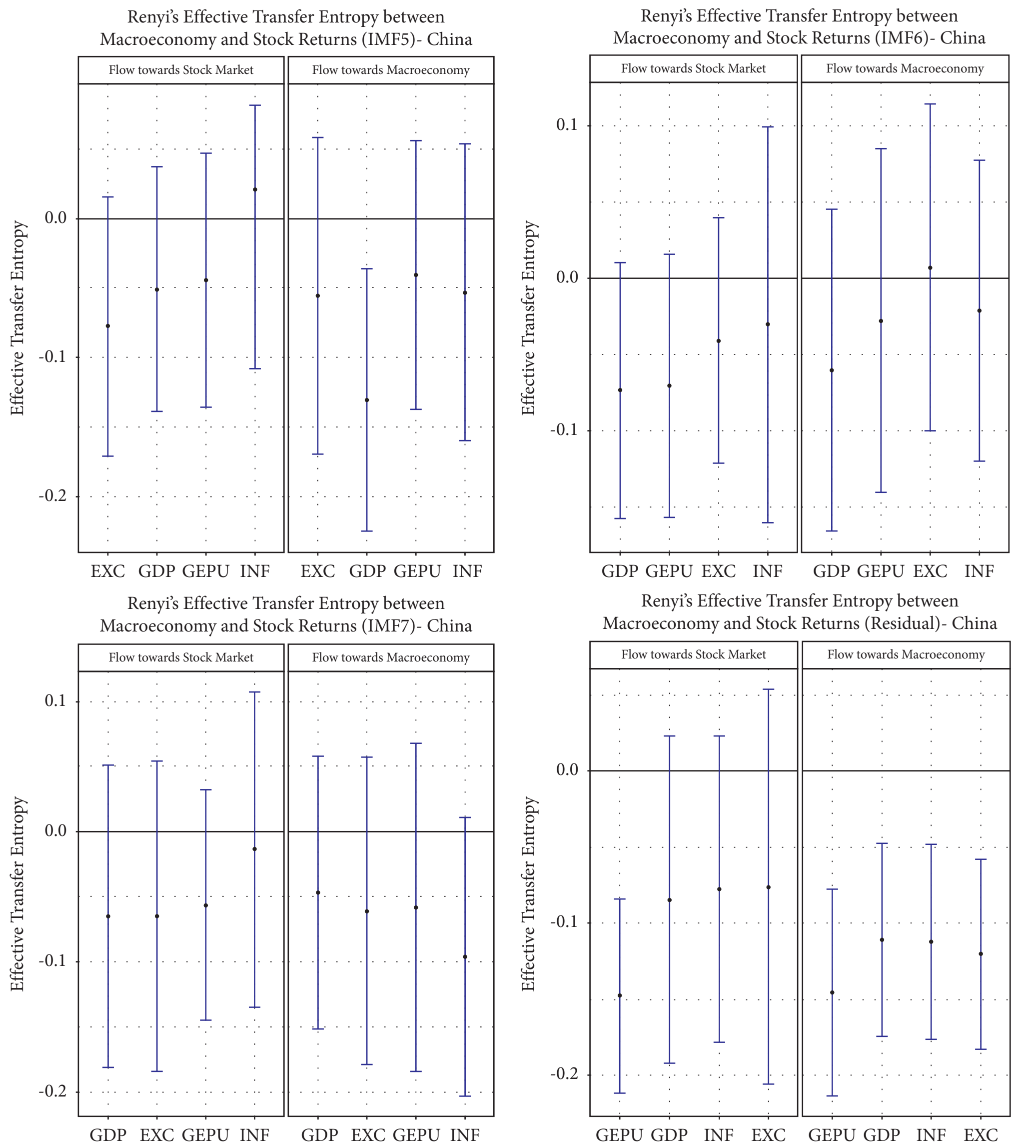

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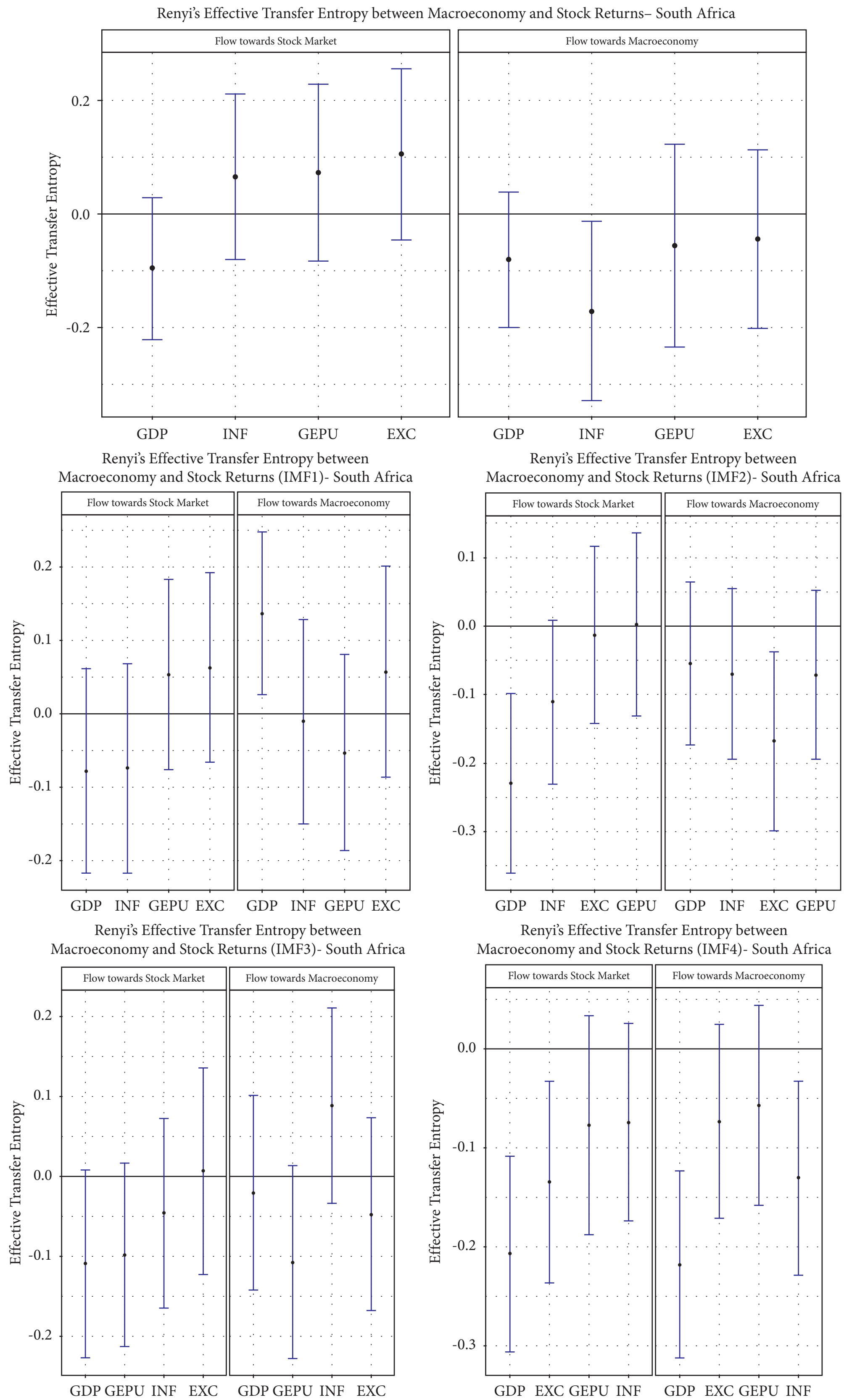
Figure 4: Decomposed macroeconomic factors and stock of China.

as GDP at IMF 5. It can be observed from the long-run that significant adverse information flows from GEPU and inflation to the stock returns of South Africa. That is, stock returns of South Africa are negatively affected by the knowledge of GEPU and inflation. The long-run influence of GEPU on stock returns of South Africa confirms the study of Asafo-Adjei et al. [46] when the bivariate wavelet technique was employed. In the case of transfer entropy, the outcome of this study on the significant flow of information between external policy uncertainty shocks and stock returns of South Africa strongly concurs the findings of Adam [68].

Table 4 presents the statistical values for the Rényi effective transfer entropy (RETE) with a null hypothesis of no significant information flow. We provide these values at varying levels of significance to offer additional insights into the information flow phenomenon which is in line with the outcomes from Figures 1–5 for the BRICS economies.

Analysis of the study was performed with a log-likelihood ratio transfer entropy which quantifies information from a probability density function to fill a gap in the extant literature on macroeconomic-stock market nexus which mostly utilise linear models. In addition, we perform information flows at different investment horizons to minimise noise from the data by applying the CEEMDAN technique which is superior to other EMD techniques. The findings generated from this study make a unique contribution to prior literature on the



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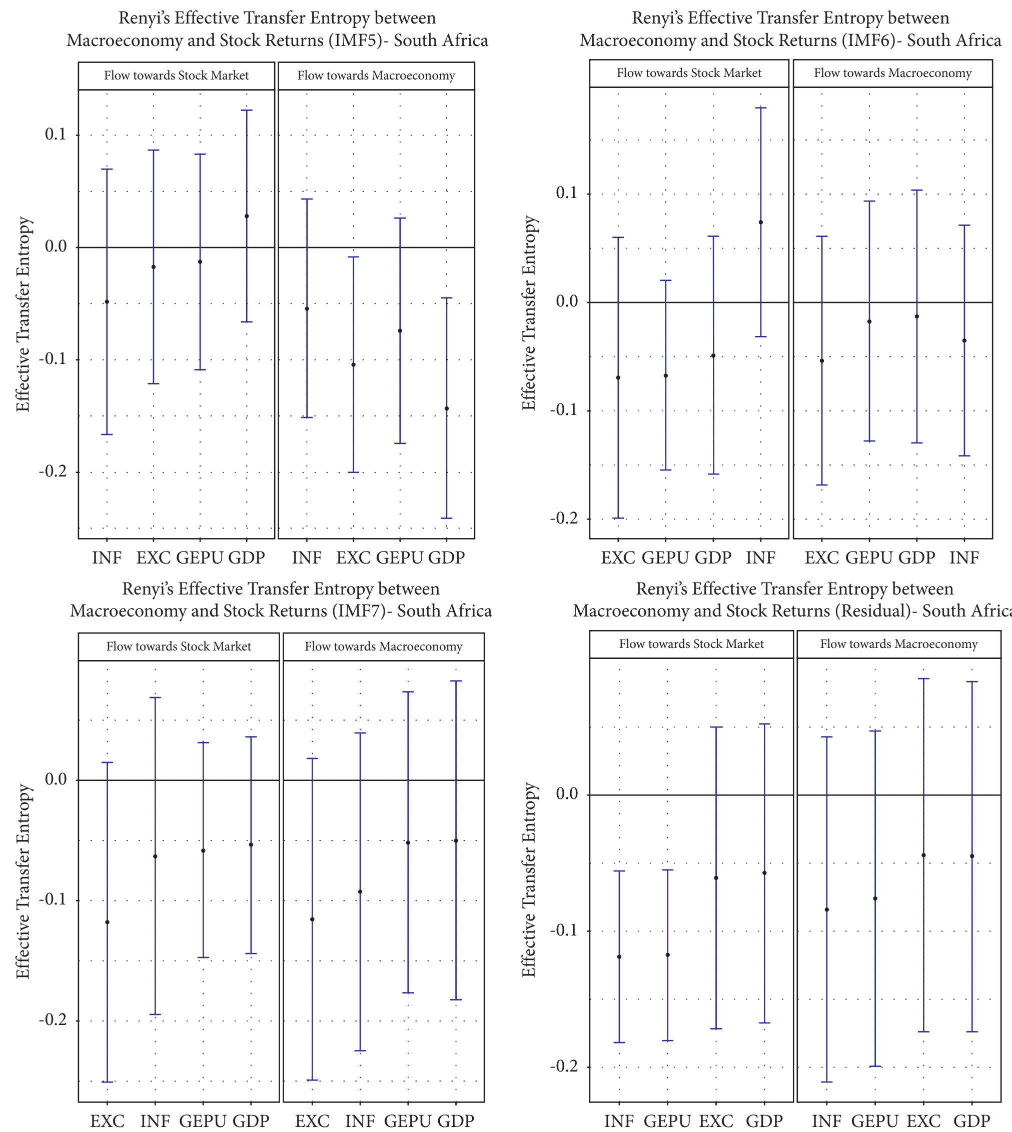

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Figure 5: Decomposed macroeconomic factors and stock of South Africa.

nexus between stock returns and macroeconomic variables in many ways. First, we responded to the nonstationary, asymmetric, and nonlinear nexus between stock returns and macroeconomic variables across investment horizons by employing the CEEMDAN-based RTE technique. Second, we found a bidirectional causality between stock returns and relevant macroeconomic indicators across investment scales to divulge that their rippling effects are heterogeneous and adaptive driving the need for a frequency-dependent estimates.

Particularly for the GEPU, which has stimulated attention from researchers, investors, and policy makers since the 2007–2009 Global Financial Crisis [46, 51, 68], we found significant negative information flows from the GEPU to stock markets of BRICS mostly in the long-term. It is obvious that stock markets of BRICS economies are susceptible to external shocks in the long-term perspective. This explains the fact that not only are local fundamentals relevant to transmit significant shocks but external shocks should also be given massive attention.

Accordingly, the main value addition of this study to prior studies is the application of methods and the presence of GEPU to assess the relevance of external and local shocks transmission in the context of BRICS economies. To the best of our knowledge, this is the first study that employs the CEEMDAN-based entropy approach to examine causality between stock returns of BRICS and relevant local and external macroeconomic indicators.

Table 4: Rényi effective transfer entropy estimates.

	Signal	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5	IMF 6	IMF 7	Residual
Brazil									
EXC -> SR	0.045	−0.013	−0.119*	−0.111*	−0.135**	−0.055	−0.138**	−0.045	−0.087
GDP -> SR	−0.010	−0.042	−0.194**	−0.189**	−0.161**	−0.089	0.015	−0.098	−0.087
GEPU -> SR	−0.003	0.058	−0.065	−0.122**	−0.194**	−0.159**	−0.117**	−0.112*	−0.144**
Inf -> SR	0.104	0.031	−0.135**	−0.188**	0.020	0.013	−0.147**	−0.058	−0.087
SR -> EXC	−0.088	−0.153*	−0.143**	−0.105	−0.059	−0.042	−0.020	−0.066	−0.128**
SR -> GDP	−0.077	0.189**	−0.005	−0.135**	−0.141**	−0.063	−0.100**	−0.020	−0.107**
SR -> GEPU	−0.068	0.120	−0.018	−0.189**	−0.064	0.027	−0.106*	0.196**	−0.151**
SR -> Inf	−.089	−0.110	0.064	−0.194**	−0.208**	0.015	0.010	−0.055	−0.112**
Russia									
EXC -> SR	0.143*	−0.016	0.012	−0.046	−0.008	−0.061	−0.070	−0.031	−0.036
GDP -> SR	−0.066	−0.001	0.011	−0.030	−0.071	−0.054	−0.073	−0.031	−0.123
GEPU -> SR	−0.013	0.024	−0.126	−0.055	−0.063	−0.051	−0.064	−0.066	−0.126**
Inf -> SR	0.015	−0.049	0.049	−0.007	−0.139**	−0.046	−0.066	−0.013	−0.120**
SR -> EXC	0.041	−0.087	−0.002	0.083	−0.093	−0.029	−0.075	−0.096	0.073
SR -> GDP	−0.157**	−0.086	−0.131**	0.109*	−0.216**	−0.097*	−0.067	−0.012	−0.121
SR -> GEPU	0.010	0.021	−0.084	−0.139**	−0.054	−0.039	−0.025	−0.057	−0.081
SR -> Inf	−0.010	−0.088	−0.058	−0.093	−0.076	−0.032	−0.049	−0.039	−0.084
India									
EXC -> SR	0.002	−0.048	−0.007	−0.039	−0.075	−0.103	0.009	−0.067	−0.121**
GDP -> SR	0.026	−0.193**	0.009	−0.211**	−0.094	−0.016	−0.054	−0.066	−0.110*
GEPU -> SR	−0.004	−0.112	0.065	−0.123*	−0.074	−0.048	−0.057	−0.058	−0.060
Inf -> SR	−0.129	−0.203**	0.208**	0.082	−0.089	−0.023	−0.056	−0.063	−0.106*
SR -> EXC	−0.090	−0.024	−0.033	−0.153**	−0.205**	−0.023	−0.128*	−0.047	−0.111*
SR -> GDP	−0.046	0.091	−0.021	−0.188**	−0.072	−0.136**	−0.053	−0.053	−0.115**
SR -> GEPU	−0.080	−0.033	−0.147*	−0.107	−0.001	−0.088	−0.035	−0.053	−0.061
SR -> Inf	−0.005	−0.027	−0.002	−0.060	0.095*	−0.151**	−0.046	−0.058	−0.112*
China									
EXC -> SR	−0.060	−0.025	0.111	−0.153**	−0.029	−0.077	−0.041	−0.065	−0.076
GDP -> SR	−0.002	−0.142	−0.041	−0.040	−0.071	−0.051	−0.073	−0.065	−0.084
GEPU -> SR	−0.018	0.001	0.013	−0.095	−0.006	−0.044	−0.070	−0.056	−0.148**
Inf -> SR	0.172**	−0.042	0.042	−0.032	−0.075	−0.014	−0.030	−0.014	−0.077
SR -> EXC	−0.018	−0.113	0.179**	−0.060	−0.084	−0.056	0.007	−0.061	−0.120**
SR -> GDP	−0.033	−0.023	−0.072	−0.087	−0.223**	−0.131**	−0.060	−0.047	−0.111**
SR -> GEPU	−0.051	−0.009	0.003	−0.024	0.030	−0.041	−0.028	−0.058	−0.145**
SR -> Inf	0.228**	−0.062	0.037	0.035	−0.129**	−0.053	−0.021	−0.096	−0.112**
South Africa									
EXC -> SR	0.106	0.062	−0.015	0.005	−0.140**	−0.021	−0.064	−0.121	−0.064
GDP -> SR	−0.096	−0.078	−0.228**	−0.114	−0.220**	0.010	−0.036	−0.057	−0.052
GEPU -> SR	0.074	0.053	−0.015	−0.090	−0.058	−0.006	−0.068	−0.058	−0.127**
Inf -> SR	0.066	−0.075	−0.110	−0.027	−0.075	−0.044	0.078	−0.063	−0.124**
SR -> EXC	−0.044	0.057	−0.173**	−0.049	−0.075	−0.107*	−0.050	−0.119	−0.049
SR -> GDP	−0.080	0.136**	−0.046	−0.033	−0.228**	−0.139**	−0.016	−0.043	−0.043
SR -> GEPU	−0.055	−0.053	−0.075	−0.110	−0.049	−0.075	−0.028	−0.049	−0.077
SR -> Infl	−0.171*	−0.011	−0.060	0.114	−0.115**	−0.061	−0.027	−0.101	−0.078

Note. *, **, and *** indicate significance at 10%, 5% and 1% levels respectively. EXC, GDP, GEPU, Inf, and SR denote exchange rate, gross domestic product, global economic policy uncertainty, inflation, and stock returns respectively. EXC -> SR denotes information flow from exchange rate to stock.

4. Conclusion

We employed the CEEMDAN-based transfer entropy to measure the direction and strength of information transfer between macroeconomic variables and stock market returns of BRICS economies at diverse time scales. In this way, we explored the multiscale information that might be ignored. Due to the nonlinearity, unbalanced, and long-ranged nature of most financial time series, we adopt a log-likelihood ratio transfer entropy which quantifies information from a probability density function. The study therefore comprehensively focused on quantifying the flow of information between macroeconomic variables and stocks while simultaneously appending noise to the residual of prior iteration in a multiscale perspective using CEEMDAN-based transfer entropy. We set q to 0.3 to account for tail events within the sampled time series demonstrating stressed markets conditions replete in financial time series of a more drop downs than high ups.

We find both bidirectional and unidirectional information flow between macroeconomic conditions and stock markets of BRICS economies at multiscale which establish the information flow theory, where two random variables are related in such a way that one variable can learn about the state of the other through observation of the other [90]. Thus, the tail dependent multiscales information flow dynamics is established in this study. Particularly for bi-causality with exchange rates, the stock-oriented and flow-oriented hypotheses are germane to this study. Again, the adverse flow of information from exchange rates to stock markets of Brazil, China, and India at certain time-scales proofs the equity parity theory of adverse movements in domestic currency due to higher investments in foreign equity holdings by domestic investors.

The responses of macroeconomic conditions to the performance of stock markets of Brazil, China, and India are highly comparable. Notwithstanding, significant negative information flows from global economic policy uncertainty to stock markets of BRICS mostly in the long-term. The adverse long-term influence of GEPU on stock markets is not far from the results obtained by prior empirical studies [46, 91]. It is not startling to find that GEPU adversely impact on stock returns of China and India because Osei et al. [92] made it clear that EPU from China and India respond quickly to a rise in value of other ASIAN countries' EPU indices, which may require possible policy uncertainty synergies and spillovers among the Asian countries. We advocate that stock markets of BRICS economies are vulnerable to external shocks and uncertainty in the long-term perspective which is contrary to the findings of Hung et al. [51, 93]. This is because BRICS economies are open to international trade and investment. Consequently, investor fear and expectations from other nations such as the US could have an adverse influence on stock markets of BRICS as found in the study of Owusu Junior et al. [35]. Accordingly, external shocks should be carefully evaluated in addition to local shocks.

Moreover, the adverse contributions of gross domestic product to the performance of stock markets are not surprising. In the life of a product, it will only be factored into GDP once. As a result, current transactions involving assets and property produced in previous eras are not taken into account when calculating current GDP. As a result, current exchanges in stocks or fluctuations in financial assets values are not included in GDP. Although GDP measures the market value of all goods and services, economic activities that skip the regular financial channels are ignored. This posits that the notion of fluctuations in the value of financial time series such as stocks is not adequately captured in GDP. Hence, in light of the demand-following hypothesis, persistence in the real growth of an economy gradually plunges the financial sector. Nonetheless, it was instructive that both the supply-side and demand-side hypotheses were crucial in this study with insights from the bi-causality dynamics between GDP and stock returns of BRICS. It is recommended that policy makers and governments should focus on the sustainability of economic growth while deploying country level policies to balance fluctuations in inflation, exchange rates, and gross domestic product to minimise the long term effect of external uncertainty shocks on the returns of BRICS stocks.

The study is limited in a few ways. First, the outcome from the CEEMDAN model is sensitive to the model parameters. Consequently, the decomposition results will be different if different parameters are used, which will affect the follow-up analysis. Notwithstanding, to minimise subjectivity in the CEEMDAN outcome by varying the model parameters, we employ the default parameter as provided in the package of Helske and Luukko [75]. Second, it is worth considering how the RTE discussed here stacks up against other correlation checks. The most common correlation tests account for lower-order correlations (such as, time-lagged cross-correlation test) or attempt to resolve the causation problem between bivariate time series (for instance, the Hacker and Hatemi-J causality test or Granger causality test) [85]. Because the RTE only compares specific elements of the underlying distributions, it indirectly deals with high-order correlations and so cannot definitively answer the causality question. Third, the RTE lacks a time dimension to be a single-scale entropy estimate as compared to other entropy models such as multiscale transfer entropy and multiscale multivariate transfer entropy. We minimise this predicament by providing an intrinsic time dimension while maintaining the averaged time responses of the variables to information flow through the CEEMDAN-based RTE approach. Through this approach, we are able to perform the analysis at various investment horizons to minimise noise as well as set the value of q depending on the general nature of economic activities over the sampled period to either offer more weights to the tails or otherwise.

The study sample included the COVID-19 pandemic period. Future studies can concentrate on the flow of information between BRICS stocks and macroeconomic variables before and during the COVID-19 pandemic period to assess how the COVID-19 has influenced this established relationship using more advanced decomposition techniques since information flows are richer at multiscales [1, 34]. The analyses could also be performed using wavelet techniques to address time and/frequency dimensions [47, 53, 93–95], or copula models [96], Markov-switching models [97], and dynamic conditional correlation [36, 98].

Data Availability

The data used in support of this study are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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