Hindawi
Complexity
Volume 2022, Article ID 1027495, 25 pages
https://doi.org/10.1155/2022/1027495

Research Article

Flights-to-and-from-Quality with Islamic and Conventional Bonds in the COVID-19 Pandemic Era: ICEEMDAN-Based Transfer Entropy

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Received 4 November 2021; Revised 1 December 2021; Accepted 24 December 2021; Published 31 January 2022

Academic Editor: Mariya Gubareva

We revisit the flight-to-quality (FTQ) and flight-from-quality (FFQ) occurrences vis-à-vis the stock-bond nexus across differing investment time scales in the COVID-19 era, using a novel technique hinged on a denoised frequency-domain transfer entropy. Our findings divulge that flights, both FTQ and FFQ, could be attained during stress periods. Generally, in the intermediate term of the COVID-19 pandemic, both Islamic and conventional bonds could act as safe havens, diversifiers, and hedges for international equities, and the same could be observed for international equities. We reiterate empirically that flights may improve the financial system's stability and robustness by allowing diversity to be effective when it is most required. The findings have financial and portfolio implications for investors considering how to deploy their investments in the COVID-19 era. Our findings may impact policymakers' responses to changes in various asset classes, allowing them to better monitor financial markets and adjust macroeconomic policies.

1. Introduction

The global economy has been severely impacted since the World Health Organization announced the COVID-19 pandemic a global health emergency. The supply of staple foods declined [1], sales fell, consumers altered their habits, output was cut, corporations were in major financial constraints, and global unemployment rates rose [2]. Such drastic changes in the global economy and business are expected to have an impact on equities as well as alternative investments. The objective of several firms within industries like tourism [3], energy and communication [4], food and hospitality [1], etc., had to be altered; instead of the regular shareholder wealth maximisation, they rather aimed to "survive" the havoc brought to business operations by the pandemic. Investors have as well been led to rebalance their portfolios and amend their investment plans [5, 6].

From the foregoing arguments, thus far, it is not surprising that stock market returns would be significantly affected. It is through this same channel that equity investors would seek safe assets or asset classes that could generate the desired returns to hedge or diversify the losses suffered from their equity holdings. This would require that investors move funds from their existing allocations into new allocation sets. This movement could be termed as a "flight" and if investors find a safe asset that fulfils their desires during the turbulent market period, then the safety of the investible funds available to investors is assured in such a period. This is what Christiansen and Ranaldo [7] and Baur and Lucey [8] refer to as “flights to quality or safety,” for which the reverse version is termed as “flight-from-quality” (FFQ) [8].

Several researchers recognise that there could be significant and differing dynamics between financial assets and markets during times of stress and turmoil and, thus, investigate the link between stock and bond prices (or returns) during periods of extreme movement, resulting in a thriving “flight-to-quality” (FTQ) literature [8–13]. These studies were focused on the past financial crises.

We propose that a revisit is made to this phenomenon during the prevailing COVID-19 pandemic, but in a unique fashion that accounts for investor complexities. Notably, we must recognise that, as a consequence of exuberant market dynamics during the COVID-19’s rowdy trading phase, stock markets will have huge information structures, which may lead to negative bubbles, as Huynh et al. [14] indicate. Due to these negative bubbles, appropriate techniques must be utilised in measuring information flow within markets. The body of knowledge holds no record for assessments of the intrinsic information that mutually drives the stock-bond nexus. Recent works on the stock-bond interrelations that cover the COVID-19 pandemic period have failed to address this issue and are also limited by insufficient data and lack of appropriate methods that incorporate investor complexities (see [5, 6, 15, 16]).

We contribute to the scanty literature—that overcome these gaps—in a novel, unique, and more appropriate approach. We employ the entropy approach inspired by the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN), a data-driven technique, to assess the flow of information between global equities and bonds from both Islamic and conventional markets, taking into consideration the complexities [5, 17, 18] in investor behaviour within Islamic and conventional markets. Investor complexities could be revealed through the application of decomposed time series so that they eliminate weak signals, leaving behind true signals only [19]. The relevancy of decomposition has been proven in several studies, inter alia, as a means of overcoming complexities—such as nonstationarity and asymmetries—in financial data [5, 20–25].

We count the following significant contributions by our study. First, our decomposition method, the ICEEMDAN, corrects the flaws of subjective wavelet decomposition, which is seldom employed to investigate correlations across time scales [22, 23, 25]. The decomposition approach also overcomes the shortfalls of the VMD and the earlier versions of the EMD approaches. Second, to our knowledge, no previous study has used transfer entropy estimations based on ICEEMDAN to analyse the information flow between the stock and bond markets in a turbulent trading period like the one presented by the COVID-19 pandemic. This paper examines the dynamic stock-bond correlations across the short-, intermediate-, and long-term horizons using the transfer entropy approach. Third, frequency decompositions provide a method for assessing the flight-to-quality and flight-from-quality phenomenon across distinct time scales given the pandemic’s ostensibly negative impact on asset returns, and we achieve this through our study. Fourth, in this study, the impact of financial market uncertainty on the stock-bond relationship is comprehensively investigated, with individual impacts of global and local stock market uncertainty, as well as domestic bond market uncertainty, taken into account. This emanates from the information flow in times of the pandemic and the way such information flow affects the stock and bond markets. Lastly, stock and bond markets’ co-movement dynamics are a major input in asset allocation investment strategies, as well as risk management and control. Investors diversify their risk by holding equities and bonds in their portfolios. As a result, examining how the two major asset classes perform during the current crisis provides insight into whether diversification is effective when it is most required.

In Section 2, a brief review of the body of knowledge is presented. We provide highlights on the methodology, the ICEEMDAN-grounded Rényi transfer entropy, in Section 3. The data employed and preliminary outputs are reported in Section 4. We analyse and present a discussion on the empirical results in Section 5. Section 6 summarises the practical implications of our results, and Section 7 concludes the study.

2. Brief Literature Review

Theoretically, financial markets have proven to respond to information [26], thereon, being tagged efficient [27, 28]. In line with the situated information flow theory (SIFT), Benthall [29] suggests that causal interrelations are retrievable between financial markets (assets) on the premise that they share mutual information. The SIFT builds up on the philosophy of Odegard [30] and the statistics of Pearl [31] to quantify the intrinsic information common to two random variables. Given two random variables, if the relationship between them could be inferred by analysing the extent to which one of the variables could learn the state of the other through observation, then Benthall [29] opines that the information shared by the variables is mutual. In the context of this study, stocks and bonds are likely to observe the behaviour of each other through the mutual and intrinsic information they share in the COVID-19 pandemic era. We propose that the interrelation between these assets and the distinct nature of these asset classes would most likely cause investors to switch funds from one asset class to the other, causing a “flight” [8–13].

In line with the adaptive and heterogenous behaviour of market participants, coupled with the intense information flow, which causes increased competition for safe assets in turbulent market periods, investors may respond differently to volatilities in markets depending on their appetite for risk as they seek to maximise (minimise) portfolio returns (losses) [32]. The above lines of argument are reminiscent of Lo’s [33] adaptive market hypothesis (AMH), the heterogenous markets hypothesis of Müller et al. [34], and Owusu Junior et al.’s [6] competitive market hypothesis (CMH). Given the portfolio allocation conflict arising from the modern portfolio theory of Markowitz [32], coupled with the AMH, HMH, and CMH, market participants—in the

COVID-19 pandemic era—are expected to take periodic portfolio decisions, which would cause a switch or blend between assets and/or asset classes, and this corroborates the "flights" phenomenon.

The "flights" phenomenon holds that the usual positive relationship between stocks and bonds could turn negative in crisis periods because, in such times, the risk premium requested by equity investors is relatively high compared to the terminal premium offered on bonds [35]. In steady or tranquil trading periods, when equity investors are confident about the future, they are more inclined towards adding on different assets or introducing new asset classes (cryptocurrencies, bonds, etc.) to their portfolios. This act creates a positive co-movement between assets and/or asset classes, like the case for stocks and bonds [36]. On the other hand, where investors are less confident and have shaken faith in the feasibility of future earnings on their equity holdings, they most likely divest part of their allocations in stocks for investments in bonds. This results in a weaker or negative co-movement between equities and bonds [36, 37].

In re-examining the "flights" phenomenon, improved and novel approaches need to be used. A few recent studies have assessed the phenomenon but bear some limitations. Tachibana [38] studies the FTQ phenomenon in a regime-switching framework. This study focused on other financial crises in the past but did not cover the COVID-19 pandemic period. Corbet, Larkin, and Lucey [39] examine the contagion impact of the COVID-19 pandemic and find the features for FTQ but their study was on cryptocurrencies and gold, leaving behind other principal assets (stocks and bonds) unexplored. Aslanidis et al. [10] investigate the FTQ phenomenon in the European context using quantile regression, which cannot incorporate and assess the effect of information flows. Papadamou et al. [36] study the FTQ phenomenon but employed a panel methodology, which cannot incorporate information flow and is also constrained by the fact that only one result is generated for all cross-sectional entities; there lie differences in cross-sections and hence, generalisation of their results may be impacted. Besides, none of the studies explores the phenomenon among the Islamic financial markets together with conventional markets. The extant studies on information flow have taken a different direction. We discuss a few of these studies as part of our review.

Theoretically, a measure of information—regarding the driving and responding transfer—may be calculated for two or more variables changing in time. This has been termed by Schreiber [40] as the transfer entropy (TE). TE has been used in many empirical studies to investigate the influence of COVID-19. Lahmiri and Bekiros [2], for instance, utilise the largest lyapunov exponent (LLE) based on the Rosenstein method and approximation entropy. The use of the technique was motivated by its tolerance for tiny samples. At this stage of the COVID-19 pandemic, however, we cannot motivate for a method based on small samples. The amount of knowledge on COVID-19 as well as stock and bond markets' frequency-domain connection in the context of information transmission is growing. Corollary to the growing dataset in the COVID-19 pandemic period, a data-driven technique would be relevant for determining plausible relationships situated on the information flow between financial markets (Benthall, 2019).

By employing the Shannon entropy (SE) wavelet transform domain, Lahmiri and Bekiros [15] investigated the influence of COVID-19 on the unpredictability of global stock spillovers. Wang et al. [22] used multiscale transfer entropy to analyse the impact of COVID-19 on major global equities, currencies, and Bitcoin. These works are handicapped, on the one hand, by small sample bias, and on the other side, they employed SE, which is prone to give comparable weights to various areas of the data distribution (see [6, 15, 16]).

To this end, we add to the scanty literature on information flows while contributing uniquely to the "flights" literature through the application of the entropy approach based on the ICEEMDAN, a data-driven technique, to examine the flow of information between global equities and bonds from both Islamic and conventional markets during the COVID-19 pandemic.

3. Methodology

Our methodological approach consists of two processes. First, the Improved Complete Empirical Ensemble Mode Decomposition with Adaptive Noise (ICEEMDAN) is employed to decompose the return series into inherent mode functions (IMFs), which represent intrinsic time and is divided into short-, medium-, and long-term periods. This decomposition facilitates the examination of the information flow concerning the stock-bond interrelations throughout a range of decision-making time horizons. Second, we employ the Rényi entropy (RE) specification to estimate effective transfer entropies (ETEs). Quantification of the flow of information between equities and bond markets is done by the RE by giving more weight to the "ends" of distributions, which corresponds to the stylised realities of financial assets. In a nonparametric fashion, these techniques handle nonstationarity, nonlinearity, and asymmetry in the series [5, 41].

3.1. ICEEMDAN. Experts from the field of economics have long understood that the connectedness of variables in terms of direction, degree, and shape is distinct across time scales [42]. Nonetheless, until recently, there were no methods available to delineate economic data series into all orthogonal time-scale constituents. Furthermore, the instruments to cope with noise, which often dominate short-term financial asset series [5, 42, 43], are now accessible. The ICEEMDAN, which is the latest member of Huang's [44] empirical mode decomposition (EMD) family, is a good example. The noise-to-signal ratio (SNR) minimisation of mode decompositions in unsteady-state signals, efficiency, and reconstruction accuracy are their strengths [45]. In comparison to the others, the ICEEMDAN presented by Colominas, Schlotthauer, and Torres [46] has the best of these properties. Together with dealing with the existence of spurious modes and the presence of residual noise in the modes, the ICEEMDAN resolves the limitations of the persistence of a significant amount of noise and comparable signal scales, which are attributable to the CEEMDAN [46]. While CEEMDAN performs a better job of eliminating noise, reconstructing the signal, and finding SNR [23], it falls short on two fronts: (i) residual noise is included in the model and (ii) spurious mode problem, as Li et al. [22] contend.

Per Li et al.'s [22] specifications, which follow from Colominas et al. [46], the ICEEMDAN algorithm is summarised as follows:

Step 1. A white-noise $\tau_1[\omega^{(i)}]$ is appended to a signal x to yield a new series

$$x^{(i)} = x + \rho_0\left(\omega^{(i)}\right), i = 1, 2, \ldots, N, \quad (1)$$

where $\omega^{(i)}$, ρ_0, and N are, respectively, the i-th white noise added, SNR, and the number of white noise appended.

Step 2. Estimation of the local mean of $x^{(i)}$ is made using EMD to retrieve the first residual

$$r_1 = \left(\frac{1}{N}\right)\sum_{i=1}^{N} M\left(x^{(i)}\right), \quad (2)$$

from which first IMF $c_1 = x - r_1$ can be obtained.

Step 3. Recursively obtain the k-th IMF $c_k = r_{k-1} - r_k$, for $k \geq 2$, where

$$r_k = \left(\frac{1}{N}\right)\sum_{i=1}^{N} M\left(r_{k-1} + \rho_{k-1}\tau_k\left(\omega^{(i)}\right)\right). \quad (3)$$

The resultant decompositions from ICEEMDAN are such that the residual noise problem is substantially decreased, as well as the mean value problem caused by the varied numbers of IMFs created by EEMD [46, 47]. It is essential to note that throughout the decompositions, the default experimental parameters (for maximum iterations, the maximum number of modes, etc.) are employed. Decompositions were carried out under the MATLAB programming framework, where the default stopping criterion was employed together with 3.2007 as the last modification, as specified by Colominas et al. [46]. In the spirit of the extant literature [5, 46–48], we report a flowchart of the ICEEMDAN decomposition technique in Figure 1.

3.2. Rényi Transfer Entropy. Hartley's [49] generic information theory gives rise to transfer entropy. Hartley's [49] theory uses an algorithm to calculate the number of symbolic sequences that may occur in a given probability distribution [50, 51]. The present works on transfer entropy are based on Shannon's [52] arithmetical communication theory as an uncertainty measure, which is derived from information theory.

The average information of each symbol in a probability distribution with different symbols of a specific experiment P_j is described as

$$H = \sum_{j=1}^{n} P_j \log_2\left(\frac{1}{P_j}\right)\text{bits}, \quad (4)$$

where n signifies the number of different symbols related to P_j probabilities [49]. The mean quantity of bits essential to optimally encode independent draws [50] may be calculated using the Shannon [52] framework (hereinafter referred to as Shannon entropy) for a discrete random variable J with $p(j)$ probabilities.

$$H_J = -\sum_{j=1}^{n} p(j)\log_2 p(j). \quad (5)$$

The quantification of the flow of information between two or more time-series procedures under the Shannon entropy paradigm is borrowed from the Kullback and Leibler [53] distance (KLD) model under the premise that two or more time-series procedures are Markov. We provide I and J as two discrete random variables with equivalent marginal probabilities of $p(i)$ and $p(j)$, as well as a joint probability of $p(i, j)$ and a dynamic stationary Markov process of order k (process I) and I (process J). The Markov property states that the probability of observing I in state i at time $t+1$ conditional on k prior observations is $p(i_{t+1}|i_t, \ldots, i_{t-k+1}) = p(i_{t+1}|i_t, \ldots, i_{t-k})$. The average bits number required to encode the observation at $t+1$ before k values are known may be expressed as

$$h_j(k) = -\sum_i p\left(i_{t+1}, i_t^{(k)}\right)\log_2 p\left(i_{t+1}|i_t^{(k)}\right), \quad (6)$$

where $i_t^{(k)} = (i_t, \ldots, i_{t-k+1})$ (analogously for procedure J). The flow of information to process I from process J is assessed in a bivariate scenario by measuring the variation from the generic Markov property $p(i_{t+1}|i_t^{(k)}) = p(i_{t+1}|i_t^{(k)}, j_t^{(I)})$, which is based on the KLD. The Shannon transfer entropy is then expressed as follows:

$$T_{J\longrightarrow I}(k,l) = \sum P\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)\log\frac{P\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}{P\left(i_{t+1}|i_t^{(k)}\right)}, \quad (7)$$

where $T_{J\longrightarrow I}$ estimates the information flow from J to I. On the other hand, the flow of information from I to J, $T_{I\longrightarrow J}$, can be derived. The net information flow, which is determined as the difference between $T_{J\longrightarrow I}$ and $T_{I\longrightarrow J}$, is the primary direction of information flow.

Although the Shannon entropy is beneficial in the financial world, it fails to assign equal weights to all potential outcomes in a probability distribution. This assumption fails to cater for fat-tails, which are common in asset pricing and returns. Despite this, the Rényi [54] transfer entropy (RE) overcomes the limitation by using a weighting parameter q. The RE may be determined using the following formula:

$$H_J^q = \frac{1}{1-q}\log_2\sum_j P^q(j), \quad (8)$$

with $q > 0$. For $q \longrightarrow 1$, RE converges to Shannon entropy. For $0 < q < 1$, thus, events with a low probability are given

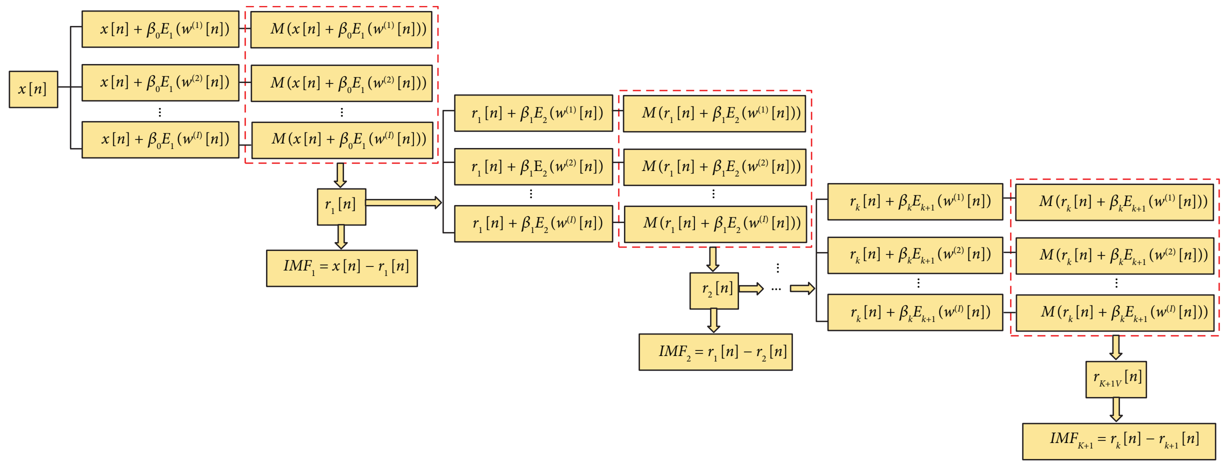


Figure 1: Flowchart of the ICEEMDAN algorithm [5, 46–48].

more weight, while for $q > 1$ the weights favour outcomes j with a higher initial probability. As a consequence, depending on the parameter q, Rényi entropy allows for varied priority to be offered to different regions of the distribution [5, 6, 50, 55]. In contrast to Shannon entropy, this is a desired aspect of RE financial applications.

In addition, with the escort distribution, $\varnothing_q(j) = p^q(j)/\sum_j p^q(j)$ for $q > 0$ to normalise the weighted distributions [56], RE is derived as

$$RT_{J\longrightarrow I}(k,l) = \frac{1}{1-q} p\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)\log_2 \frac{\sum_i \varnothing_q\left(i_t^{(k)}\right)P^q\left(i_{t+1}|i_t^{(k)}\right)}{\sum_{i,j}\varnothing_q\left(i_t^{(k)}, j_t^{(I)}\right)P^q\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}. \tag{9}$$

Note that the Rényi transfer entropy calculation might yield negative estimates. Noting the history of J, in this case, suggests significantly extra uncertainty than noting the history of I only would imply. Negative numbers imply higher risks in the context of our study, whereas positive ones suggest fewer risks.

Transfer entropy estimations are prone to bias in small samples [57]. The effective transfer entropy (ETE) could correct this and may be calculated as follows:

$$\mathrm{ETE}_{J\longrightarrow I}(k,l) = T_{J\longrightarrow I}(k,l) - T_{J\,\text{shuffled}\longrightarrow I}(k,l), \tag{10}$$

where the transfer entropy using stumbled forms of the time series J is denoted by $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$. The procedure removes the time series serial dependence of J while retaining the statistical dependence between J and I by repeating random draws from the observed time series J and realigning them to form a new time series. This causes $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$ to converge to zero as the sample size grows, and any nonzero value of $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$ is caused by small sample effects. As a consequence, recurring shuffles and the mean of the shuffled transfer entropy approximations across all repetitions may be used as a small sample bias estimator. To get bias-corrected effective transfer entropy estimates, they are deducted from the RE estimations.

The Markov block bootstrap approach may be used to establish the statistical significance of transfer entropy estimations. Unlike shuffling, this keeps the dependencies inside the variables J and I, but removes the statistical dependencies between them. As a result, per the null hypothesis of no information flow, bootstrapping produces a distribution of transfer entropy estimates that may be examined. $1-\widehat{q}T$ yields the related $p-$value where $\widehat{q}T$ specifies the quantile of the simulated distribution generated by the relevant transfer entropy estimations (see, [6, 50]).

Finally, because transfer entropy techniques were designed to cope with discrete data, the framework's continuous data must be discretised. This is accomplished by dividing the data series into a finite number of bins, a technique known as symbolic encoding [5, 6, 50]. The symbolically encoded time series (i.e., discrete) for a quantity of bins n and bounds $q_1, q_2, q_3, \ldots, q_{n-1}$ $(q_1 < q_2 < q_3 < \ldots < q_{n-1})$ and continuous observed time-series data y_t, may be represented as

$$S_t = \begin{cases} 1 & y_t \le q_1 \\ 2 & q_1 < y_t < q_2 \\ \vdots & \\ n-1 & q_{n-2} < y_t < q_{n-1} \\ n & y_t \ge q_{n-1}. \end{cases} \tag{11}$$

When choosing the number of bins (Behrendt et al. [50] offer a more complete explanation), the magnitude and distribution of the studied time series must be taken into account. Because tailed data are crucial, binning is usually based on pragmatic quantiles of the left and right tails. Using the empirical quantiles of 5% and 95% as the lower and upper bounds of the bins, this is easily achieved. As a result, there are three symbolic encodings: negative extreme returns (lower tail) are in the first bin (0.05), positive extreme returns (upper tail) are in the third bin (0.95), and normal returns are in the second bin (intermediate, 0.90). Using the chain rule on the symbolic encoding, conditional probabilities may be expressed as proportions of joint probability. Consequently, the probabilities in equations (7) and (9) may be calculated using the relative frequencies of all likely realisations.

4. Data and Preliminary Analysis

From January 02, 2020, to September 08, 2021, we employ daily 10-Year bond yield indices of 5 key Islamic (India, Indonesia, Malaysia, Pakistan, and Qatar) and G4 (Canada, Italy, the UK, and the USA) markets (All bond markets were selected based on the availability of data for the study period. The remaining 3 markets from the G7 group had negative yield returns such that their inclusion in the study would result in fewer data points, for which the methods may not suffice.), as well as daily global equity indices for 5 market blocs (BRIC, developed markets index, emerging markets index, Europe Index, and Global market composite index). The data on bond yield and global stock indices were all supplied by *EquityRT*. Table 1 provides a descriptive summary of all bond yield and global equity indices' returns. The returns were computed as the log difference for successive equities indices using the formula

$$r_t = \log(P_{t+1}) - \log(P_t), \tag{12}$$

where r_t is the return from period t to $t+1$; P_t and P_{t+1} are data points at the respective periods t and $t+1$.

To make comparisons easier, all of the series were matched by date to create a balanced group.

To acquire a comprehensive knowledge of the statistical distribution of returns, a peek at the behavioural trends of the examined bond yield and stock indices is essential. Figure 2 (raw series (left) return series (right)) visually depicts the trajectory of the data series of the bond yield and global stock indices across the studied period.

In the early days of the COVID-19 pandemic, which was rapidly growing in terms of confirmed cases, all bond yield and global equity indices seemed to have a significant negative trend. The markets have been more stable after some time into the pandemic, with rising inclinations evident since certain countries implemented lockdown in early February 2020. Unlike the global equities indices which have been picking upward trends, the bond yields seem to have a more relaxed trend after the deep downturn between February and March in the early days of the COVID-19 pandemic. We find the unfavourable correlation between pandemics and financial markets to be intuitive and comprehensible. The volatilities in bond yield for the G4 markets tend to be higher than in Islamic markets. It is not surprising that whereas almost all the Islamic bonds achieved a positive (zero) mean (see Table 1), G4 bond yields achieved negative means over the studied period.

A glance at Table 1's descriptive summary of the return series reveals numerous noteworthy aspects of the bond yield and global stock market return rates under study. All return series deviate normality, based on the Jarque-Bera statistics (Normtest.W) ($p < 0.05$ for all bond yield and global stock markets).

Throughout the studied period, all Islamic bond yields had positive averages close to zero with Qatar being an exception. The G4 bond yield had negative averages. Except for Pakistan and Canada, all bond yield markets achieved a positive skewness, which suggests that the extra positive bond yield returns outweighed the excessive negative returns in the period. The reverse is true for the Pakistani and Canadian bond yields. Concerning the global equities, all market blocs achieved a similar positive average. As a result, none of the market blocs analysed had seen losses in their equities on average. The negative skewness figures for all market blocs show that in the studied COVID-19 era, bigger losses outnumbered larger earnings on equities markets across the globe. This observation reignites the relevance of revisiting the FTQ and FFQ phenomena in the COVID-19 era. Thus far, the European stock index—with the greatest negative skewness—seem to have suffered more losses than other market blocs in the studied COVID-19 period. From the kurtosis statistics, all return series showed a leptokurtic behaviour, suggesting that relative to a normal distribution, the returns have a lot of tails. This is hardly surprising, given the stylised fact about financial assets [58].

5. Results and Discussion

The study's main objective is presented and discussed in this part of the paper. Information flow between the financial markets under study is analysed. We look at the two-way (bidirectional) flow from equities to the bond markets and from bonds to the equities markets. The Rényian entropy technique produces effective transfer entropies (ETEs) that are both negative (high risk) and positive (low risk). When the second asset (bond yield) negatively receives information flow from the first asset (stocks), a flight is feasible. It means that the second asset is less risky to shocks from the first asset and hence, holders of the first asset could flock to the second asset for safety. The opposite holds for the second asset when the first asset receives shocks. We adopt a fault weight of 0.30 to account for fat-tails in the return series, which corresponds to the stylised fact vis-à-vis financial returns [58]. We also provide results in the frequency domain and at the composite level. In the latter, IMFs 1–6 and Residual are utilised to indicate intrinsic times: short-, intermediate-, and long-term dynamics, with the residual reflecting the long-term trajectory, which reveals the underlying character of the relevant series. We could evaluate either market's dynamic reaction to the other using the time scales. We could distinguish between or link composite entropies and the entropies for the IMFs as follows. Composite entropies represent the case where there are no asymmetries in the stock-bond relationship, that is, they symmetrically observe each other based on mutual information flow. The IMFs, on the other hand, represent the case where asymmetries exist in the stock-bond interrelations, catering for complexities in the behaviour of market participants.

Black spots inside red (blue) bars represent ETEs at the composite (frequency-domain) level. Figure 3 shows the ETEs in the composite state, and Figure 4 portrays them in the frequency-domain states. At the endpoints of the red or blue bars are the 95% confidence boundaries. As a consequence, if these confidence bounds are in the positive or

Table 1: Descriptive summary of bond yield and global stock indices returns.

Country/market	Obs[a]	Min	Max	Mean	SD	Skewness	Kurtosis[b]	Normtest.W*
Bond yield								
India	264	−0.039	0.045	0.000	0.008	0.031	7.625	0.851
Indonesia	264	−0.060	0.061	0.000	0.013	0.287	7.298	0.838
Malaysia	264	−0.071	0.081	0.000	0.017	0.026	5.519	0.876
Pakistan	264	−0.104	0.030	0.000	0.012	−4.220	31.158	0.585
Qatar	264	−0.164	0.250	−0.001	0.035	1.727	15.773	0.759
Canada	264	−0.310	0.200	−0.002	0.054	−0.547	4.699	0.944
Italy	264	−0.237	0.381	−0.001	0.062	0.955	7.520	0.898
UK	264	−0.372	0.445	−0.003	0.118	0.305	1.483	0.976
USA	264	−0.350	0.313	−0.001	0.053	0.057	12.157	0.855
Global stocks								
BRIC	264	−0.081	0.053	0.001	0.015	−1.084	5.270	0.919
DEVMI	264	−0.103	0.083	0.001	0.015	−1.486	15.589	0.773
EMGMI	264	−0.079	0.047	0.001	0.014	−1.385	7.287	0.897
EURMI	264	−0.140	0.084	0.001	0.017	−2.463	21.557	0.766
GLOBALMI	264	−0.122	0.087	0.001	0.025	−0.709	3.761	0.941

Notes: [a] = observations; [b] = excess kurtosis; * $p < 0.01$; *SD* = standard deviation. BRIC is the market index for BRIC economies, DEVMI is the developed markets index; EMGI is the emerging markets index; EURMI is the Europe index, and GLOBALMI is the global market composite index.

negative sections, we must reject the null hypothesis of “no information flow.” If there is any overlap at the origin, any information flow is insignificant. The ETEs in Figures 3 and 4 as well as in Figure 5 are numerically reported in Table 2.

There happen to be more insignificant transfer entropies between bonds and global equities at the composite level. In the case of the BRIC market, the flow toward Islamic and conventional bonds are mostly positive, suggesting that shocks to the equities in BRIC could induce shocks in Islamic and conventional bonds and hence provide no avenue for flights to occur per the rudiments of the “flights” phenomenon [8–13]. A reverse scenario is spotted from the flow from bonds to BRIC equities, where there exist several negative transfer entropies, suggesting that shocks from the Islamic and conventional bond markets may not translate directly to BRIC equities. This is favourable for diversification, in line with the flights (specifically, the FFQ of [8]) phenomenon but lacks statistical significance. These observations with BRIC equities are similar to the equities of emerging markets (EMGMI) and a large extent to global equities (GLOBALMI).

Between developed and European equities markets, there exist more negative transfer entropies both for flow towards bonds and flow towards equities, suggesting that flights could occur between bonds and stocks from the developed and European markets. However, these flights may be insignificant due to the insignificant ETEs at the composite level. Since investors’ decisions change across time scales, it is essential that assessments of the significance of these information flows are judged from the frequency domain. Besides, the COVID-19 pandemic period has seen several macroeconomic policy revisions, which according to Andersson et al. [35], Papadamou et al. [36], and Skintzi [59] affect the stock-bond interrelations across time. Therefore, we turn to the ETEs at the frequency-domain level (see the Appendix for ETEs at IMFs 2, 4, and 6) (see Figures 4 and 5).

Commensurate with the extant literature [5, 6, 43, 60–62], we define IMFs 1–3 to represent short-term dynamics, IMFs 4–6 to represent intermediate-term dynamics, and IMF Residual to represent long-run dynamics. The short term, according to Yang et al. [43], is characterised by investor attitudes and market dynamics; the intermediate-term by the impact of key proceedings; and the long term by fundamental characteristics. Practically, the IMFs—in the context of this study—help in distinguishing between the market dynamics for Islamic and conventional bond and stock markets, which are necessary to determine or predict how shocks to one market (stock or bond) affect the other (bond or stock) across asymmetric periods. We could determine, from the entropies of the residual, whether or not market dynamics in the short and intermediate investment horizons persist through the long-term trend. In uncertain periods like the one occasioned by the COVID-19 pandemic, identifying these dynamics is essential for market participants such that we could predict the response of individual investors, speculators, or hedgers, as well as institutional investors. The composite entropies cannot suffice in resolving this research problem because its usage connotes symmetric information flow, which means that investors respond to market dynamics equally. That is, the application of composite data series and the resultant composite entropies only further suggests that there are no complexities in investor behaviour or response, and this largely contradicts the AMH, HMH, and the CMH.

Also, given that bubbles in financial markets during Black Swan periods are highly persistent, there is the need to decompose the composite data series into intramode functions that would alleviate, to the barest minimum, noisy observations and produce essential entropies at the various investment horizons. In addition, given the bubbles in composite data series, noise may inhibit true signals, which may affect the results of the study, resulting in biased conclusions. Decomposing composite data series into IMFs reduces noise or weak signals and ensures that true signals are maintained [63, 64], which aid in generating improved results [5, 6]. Thus, there is the need to employ an

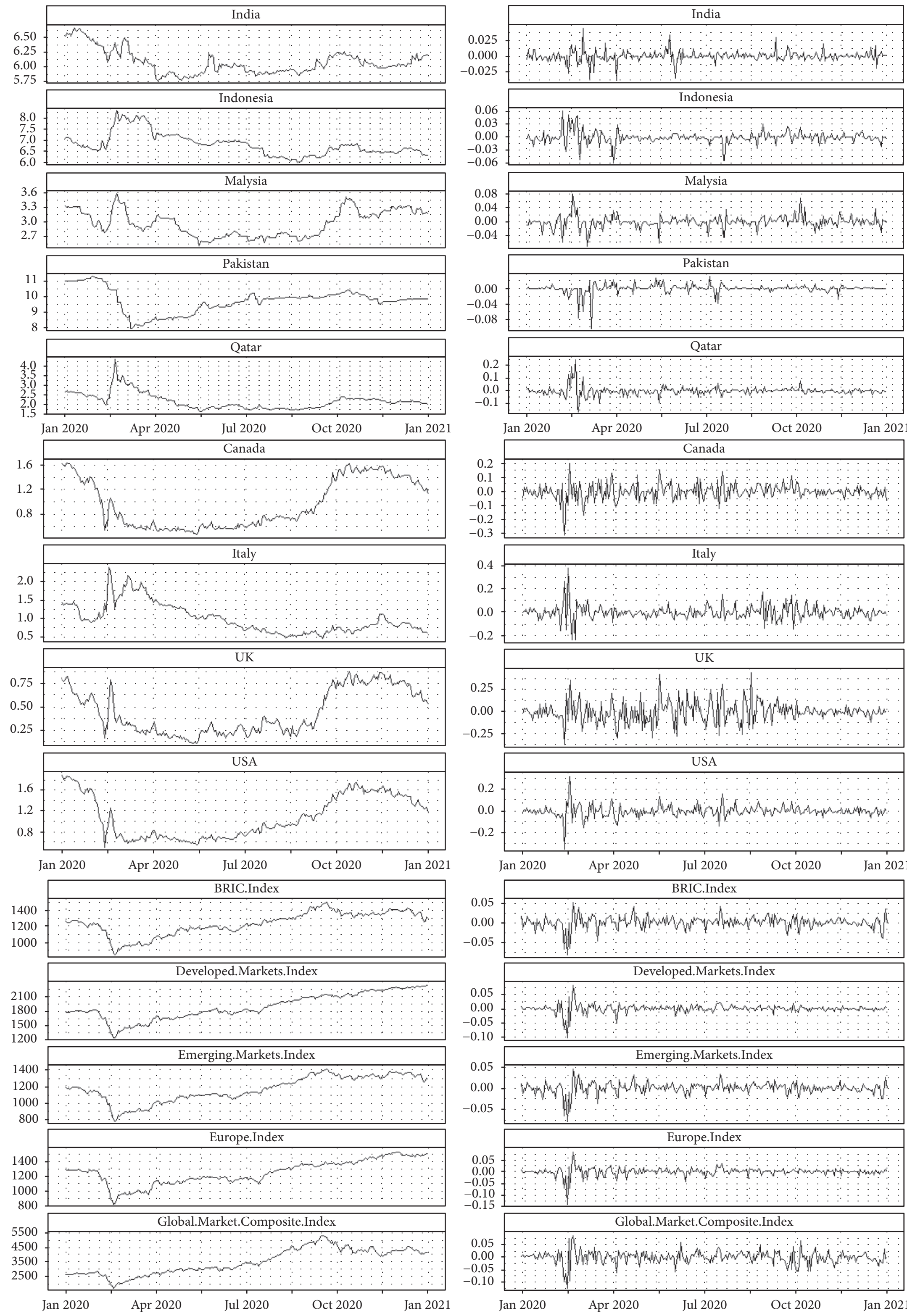


Figure 2: Trajectories of Islamic and conventional bond yield and global stock indices.

appropriate decomposition technique. This substantiates the relevancy of the application of decomposed data series (i.e., IMFs and the residual) through the ICEEMDAN approach in this study to yield frequency-domain entropies.

Generally, from Figure 4, Islamic and conventional bonds are mostly negative recipients of shocks from global equities, suggesting that significant flights could be embarked upon by equity investors from global equities.

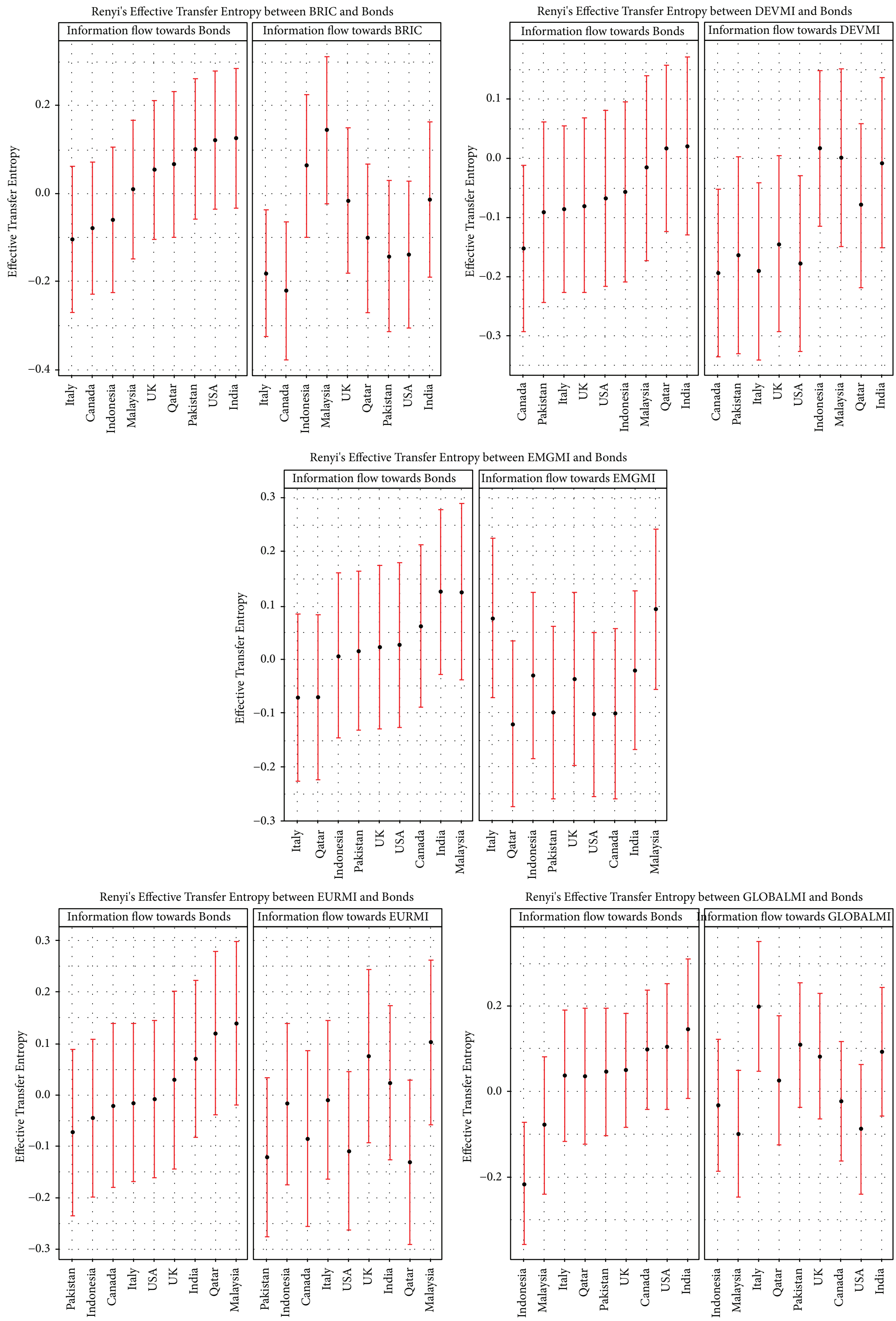
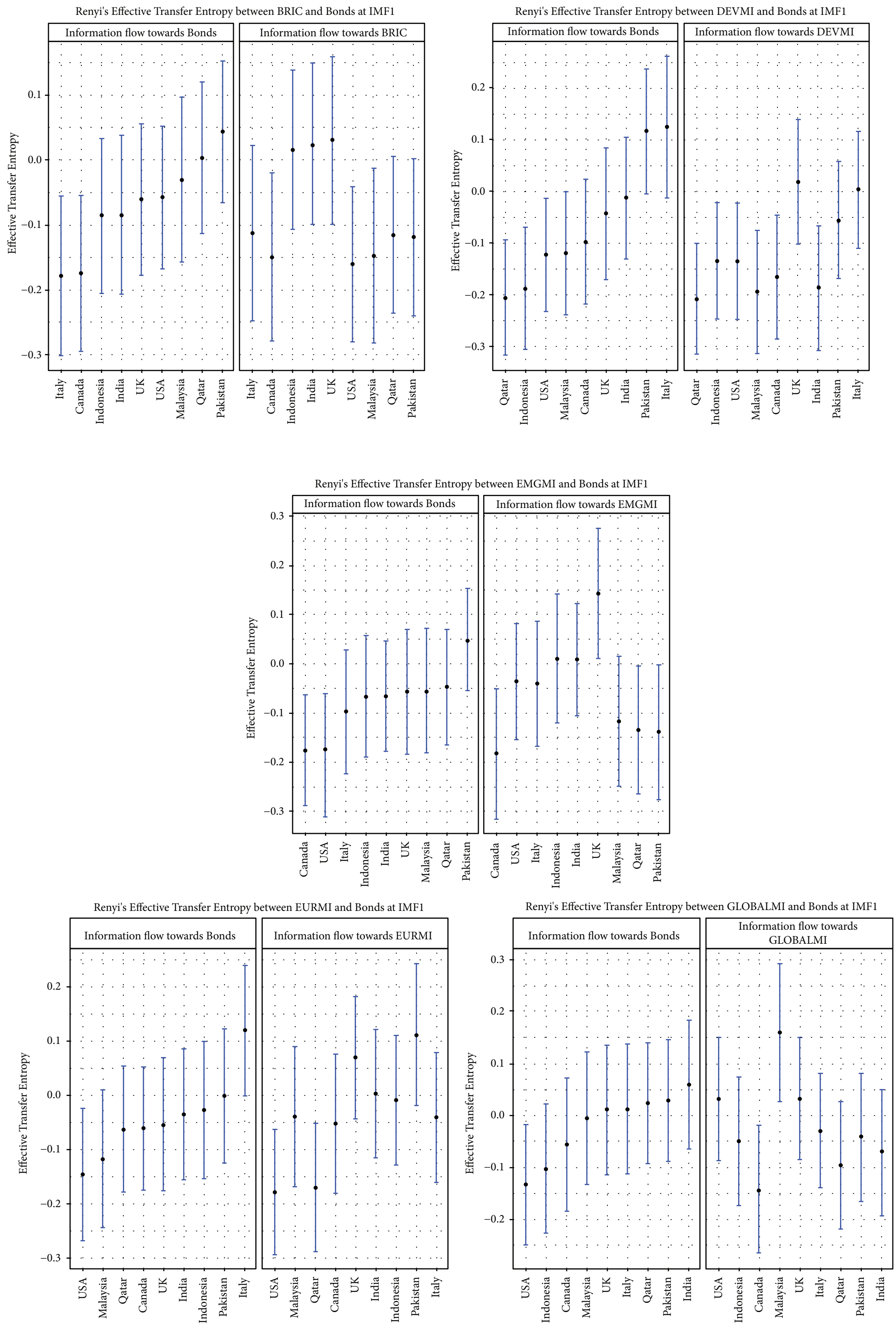
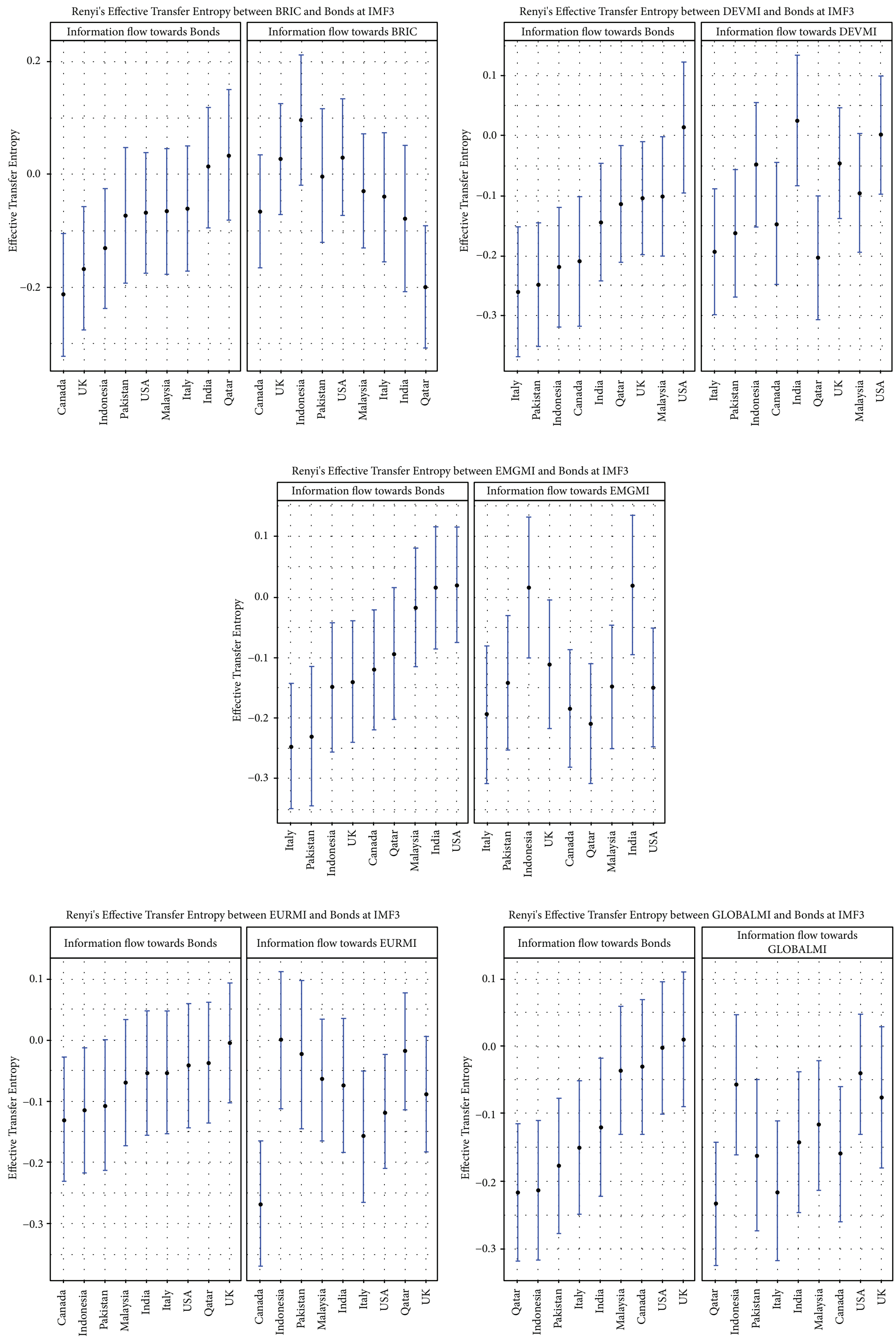


Figure 3: Transfer entropies between bonds and global equities at the composite level. (a) Renyi's effective transfer entropy between BRIC and bonds, (b) Renyi's effective transfer entropy between DEVMI and bonds, (c) Renyi's effective transfer entropy between EMGMI and bonds, (d) Renyi's effective transfer entropy between EURMI and bonds, and (e) Renyi's effective transfer entropy between GLOBALMI and bonds.



(a)

Figure 4: Continued.



(b)

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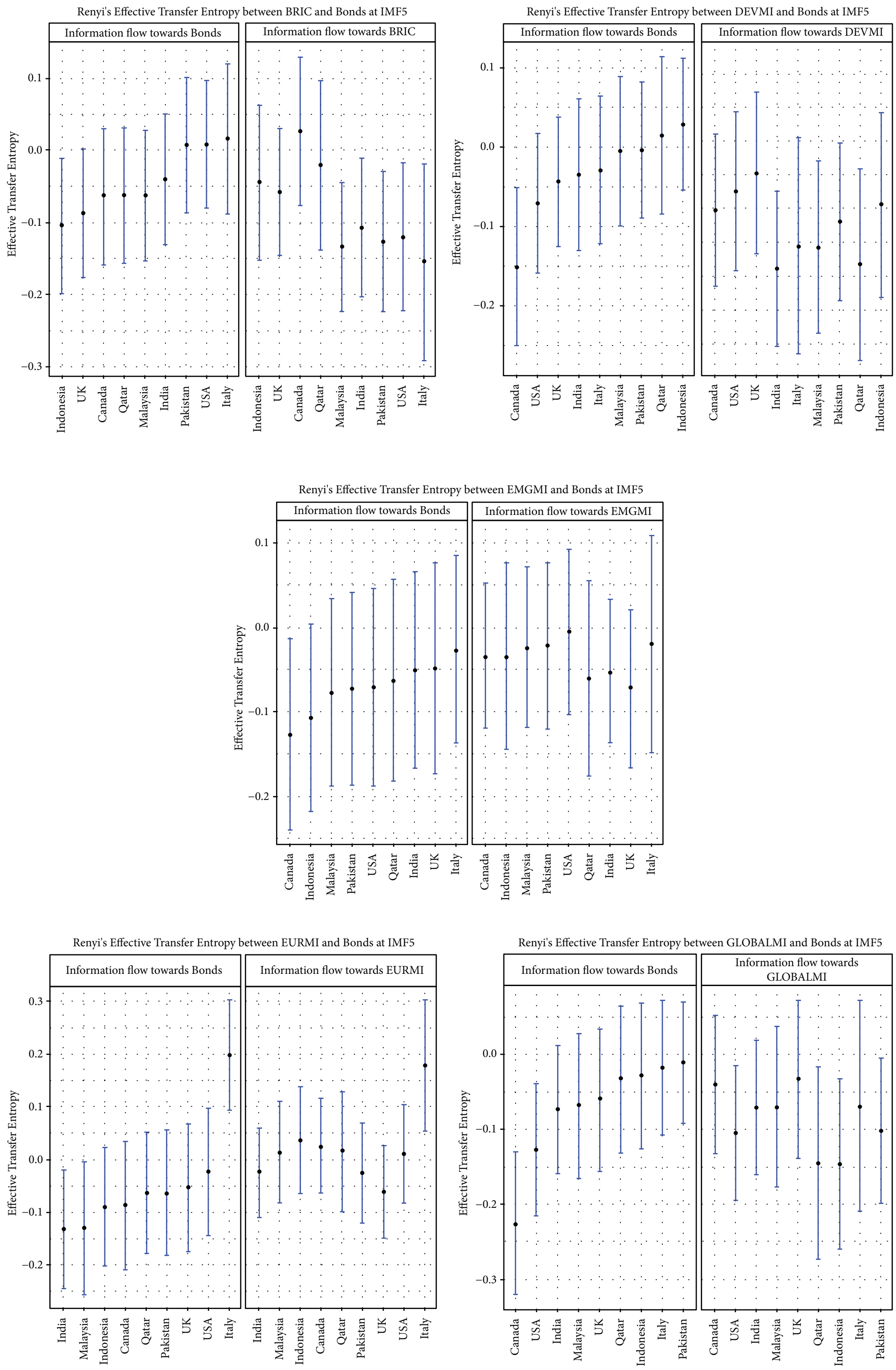

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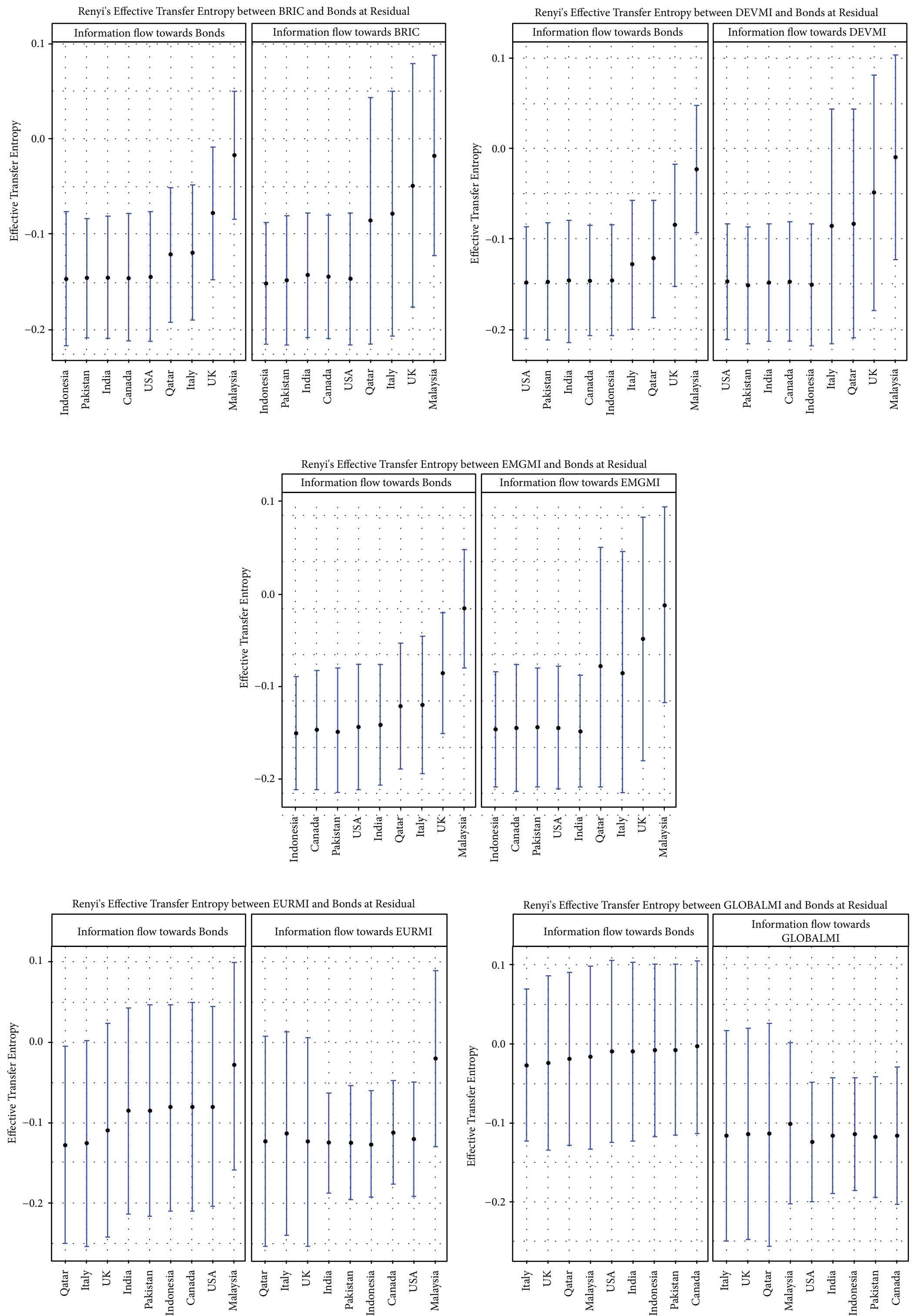
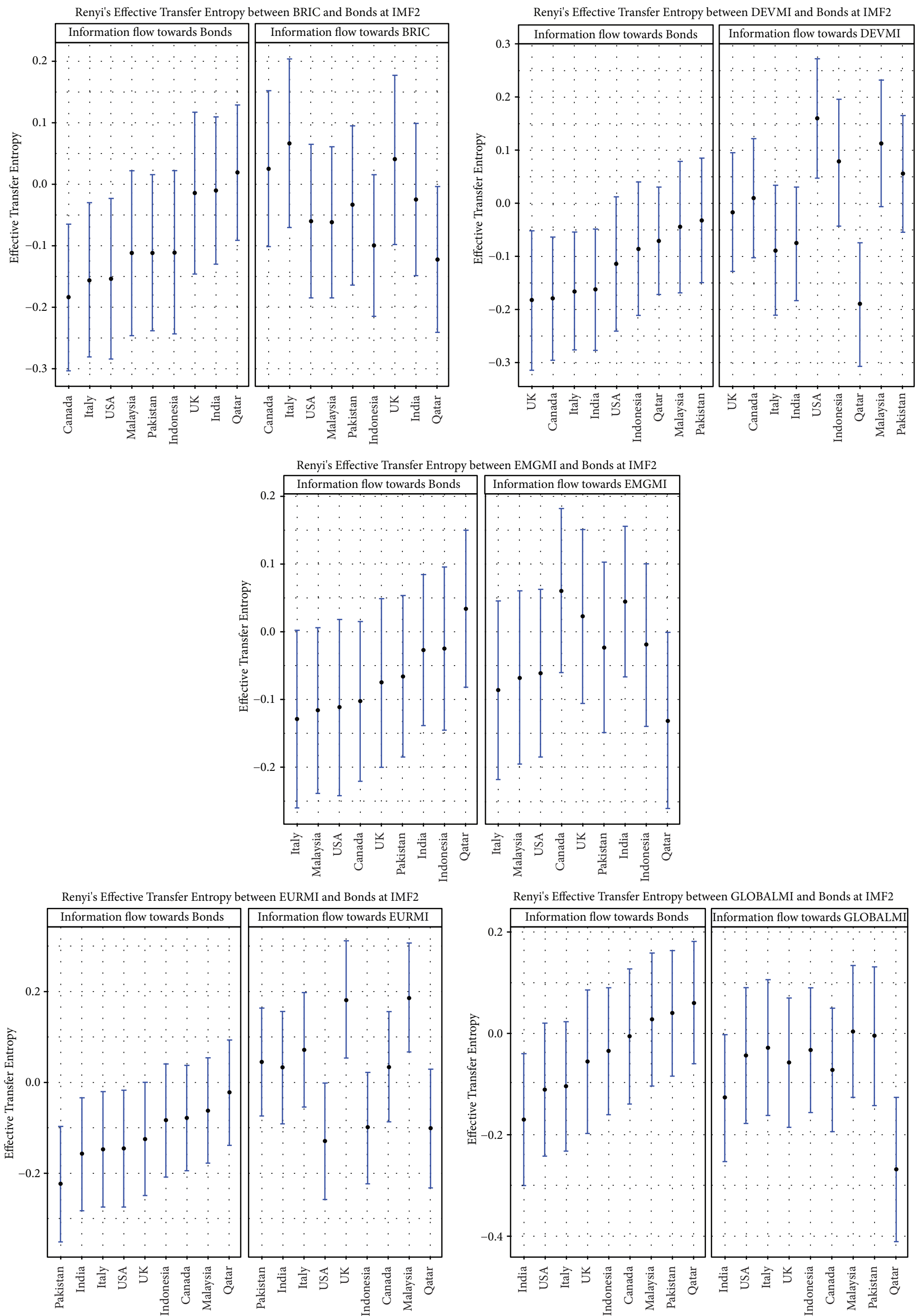


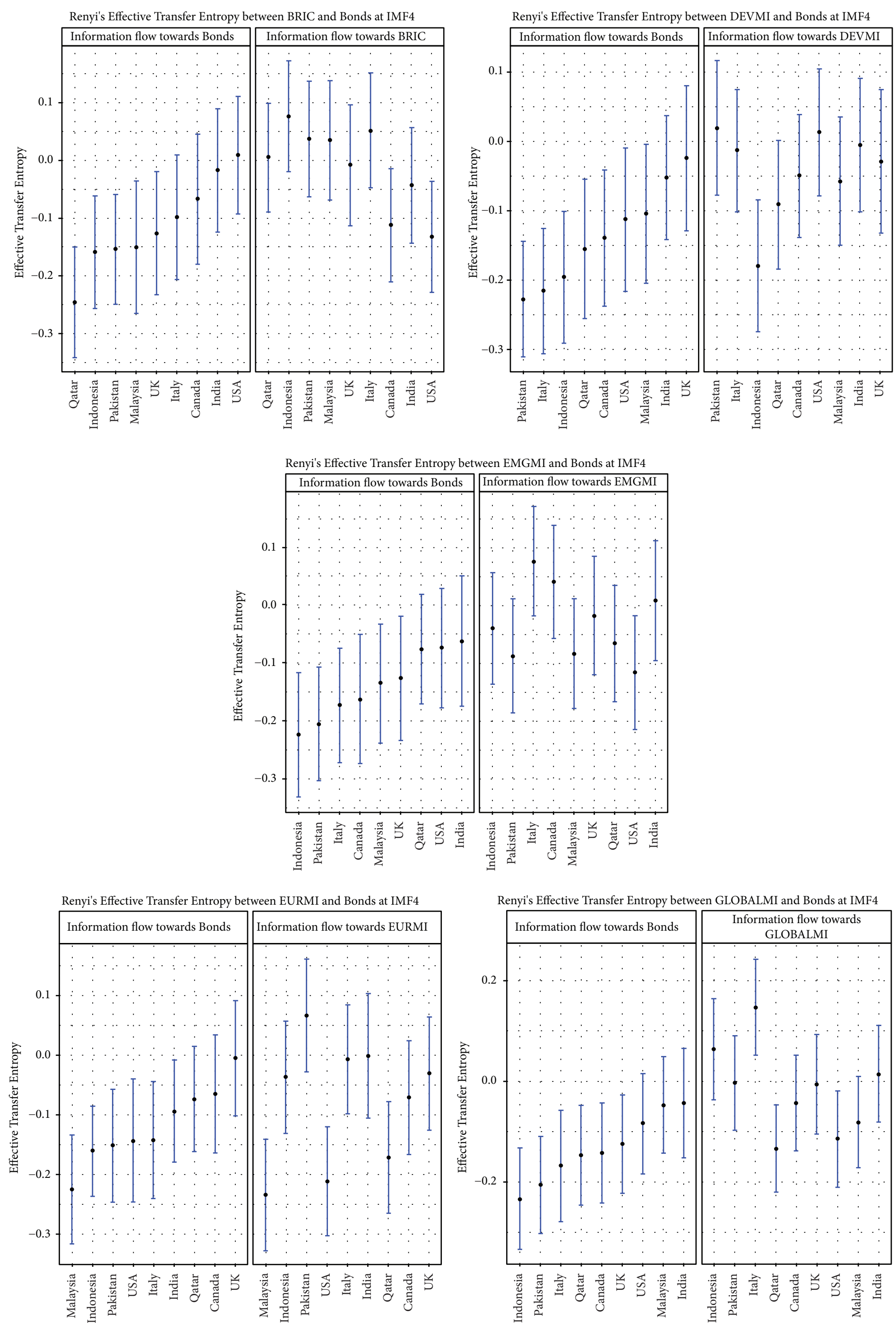
(d)

FIGURE 4: Transfer entropies between bonds and global equities at the frequency-domain level (IMFs 1, 3, 5, and residual). (a) Renyi's effective transfer entropy between BRIC and bonds at IMF1, (b) Renyi's effective transfer entropy between DEVMI and bonds at IMF1, (c) Renyi's effective transfer entropy between EMGMI and bonds IMF1, (d) Renyi's effective transfer entropy between EURMI and bonds at IMF1, (e) Renyi's effective transfer entropy between GLOBALMI and bonds at IMF1, (f) Renyi's effective transfer entropy between BRIC and bonds at IMF3, (g) Renyi's effective transfer entropy between DEVMI and bonds at IMF3, (h) Renyi's effective transfer entropy between EMGMI and bonds at IMF3, (i) Renyi's effective transfer entropy between EURMI and bonds at IMF3, (j) Renyi's effective transfer entropy between GLOBALMI and bonds at IMF3, (k) Renyi's effective transfer entropy between BRIC and bonds at IMF5, (l) Renyi's effective transfer entropy between DEVMI and bonds at IMF5, (m) Renyi's effective transfer entropy between EMGMI and bonds at IMF5, (n) Renyi's effective transfer entropy between EURMI and bonds at IMF5, (o) Renyi's effective transfer entropy between GLOBALMI and bonds at IMF5, (p) Renyi's effective transfer entropy between BRIC and bonds at residual, (q) Renyi's effective transfer entropy between DEVMI and bonds at residual, (r) Renyi's effective transfer entropy between EMGMI and bonds residual, (s) Renyi's effective transfer entropy between EURMI and bonds at residual, and (t) Renyi's effective transfer entropy between GLOBALMI and bonds at residual.



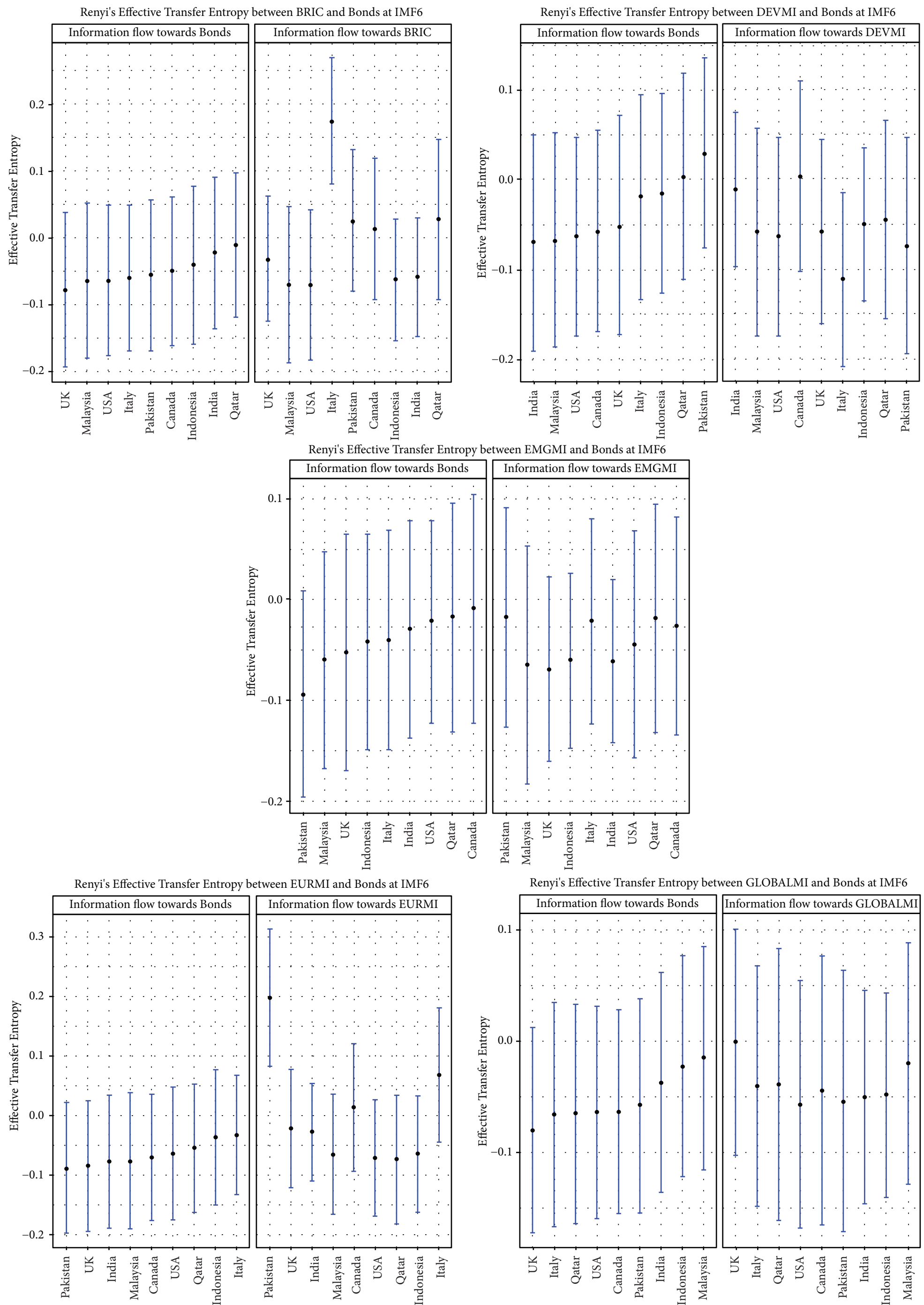
(a)

FIGURE 5: Continued.



(b)

Figure 5: Continued.



(c)

FIGURE 5: Transfer entropies between bonds and global equities at the frequency-domain level (IMFs 2, 4, and 6). (a) Renyi's effective transfer entropy between BRIC and bonds at IMF2, (b) Renyi's effective transfer entropy between DEVMI and bonds at IMF2, (c) Renyi's effective transfer entropy between EMGMI and bonds at IMF2, (d) Renyi's effective transfer entropy between EURMI and bonds at IMF2, (e) Renyi's effective transfer entropy between GLOBALMI and bonds at IMF2, (f) Renyi's effective transfer entropy between BRIC and bonds at IMF4, (g) Renyi's effective transfer entropy between DEVMI and bonds at IMF4, (h) Renyi's effective transfer entropy between EMGMI and bonds at IMF4, (i) Renyi's effective transfer entropy between EURMI and bonds at IMF4, (j) Renyi's effective transfer entropy between GLOBALMI and bonds at IMF4, (k) Renyi's effective transfer entropy between BRIC and bonds at IMF6, (l) Renyi's effective transfer entropy between DEVMI and bonds at IMF6, (m) Renyi's effective transfer entropy between EMGMI and bonds IMF6, (n) Renyi's effective transfer entropy between EURMI and bonds at IMF6, and (o) Renyi's effective transfer entropy between GLOBALMI and bonds at IMF6.

Table 2: Rényian transfer entropies between bonds and global equities.

	Composite		IMF.1		IMF.2		IMF.3		IMF.4		IMF.5		IMF.6		Residual	
	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se
BRIC																
BRIC->Canada	−0.080	0.091	−0.174	0.073	−0.184	0.073	−0.215	0.067	−0.068	0.068	−0.064	0.057	−0.050	0.068	−0.145	0.041
Canada->BRIC	−0.221	0.095	−0.150	0.079	0.026	0.077	−0.066	0.061	−0.112	0.060	0.027	0.062	0.013	0.065	−0.144	0.039
BRIC->India	0.126	0.096	−0.084	0.075	−0.010	0.073	0.013	0.065	−0.017	0.065	−0.040	0.055	−0.023	0.069	−0.145	0.039
India->BRIC	−0.014	0.107	0.025	0.076	−0.025	0.075	−0.078	0.079	−0.043	0.061	−0.107	0.058	−0.060	0.054	−0.143	0.040
BRIC->Indonesia	−0.059	0.101	−0.086	0.072	−0.110	0.081	−0.132	0.065	−0.159	0.059	−0.104	0.057	−0.040	0.072	−0.146	0.043
Indonesia->BRIC	0.064	0.098	0.015	0.075	−0.099	0.070	0.096	0.070	0.076	0.058	−0.045	0.065	−0.063	0.055	−0.151	0.039
BRIC->Italy	−0.104	0.101	−0.178	0.075	−0.156	0.077	−0.061	0.068	−0.099	0.066	0.016	0.064	−0.060	0.066	−0.119	0.043
Italy->BRIC	−0.181	0.088	−0.113	0.082	0.067	0.084	−0.040	0.070	0.052	0.060	−0.155	0.083	0.175	0.057	−0.078	0.078
BRIC->Malaysia	0.009	0.096	−0.030	0.077	−0.111	0.082	−0.066	0.068	−0.150	0.070	−0.062	0.055	−0.065	0.070	−0.017	0.041
Malaysia->BRIC	0.144	0.102	−0.147	0.081	−0.061	0.075	−0.029	0.062	0.035	0.062	−0.134	0.054	−0.071	0.071	−0.018	0.064
BRIC->Pakistan	0.102	0.097	0.043	0.067	−0.111	0.077	−0.073	0.073	−0.154	0.058	0.008	0.057	−0.056	0.069	−0.146	0.038
Pakistan->BRIC	−0.142	0.105	−0.119	0.074	−0.034	0.079	−0.002	0.072	0.037	0.061	−0.126	0.059	0.025	0.064	−0.148	0.041
BRIC->Qatar	0.067	0.100	0.004	0.071	0.020	0.067	0.034	0.070	−0.245	0.058	−0.062	0.057	−0.011	0.066	−0.121	0.043
Qatar->BRIC	−0.101	0.103	−0.116	0.073	−0.122	0.072	−0.200	0.066	0.005	0.057	−0.020	0.071	0.027	0.073	−0.085	0.079
BRIC->UK	0.055	0.096	−0.061	0.071	−0.014	0.080	−0.168	0.066	−0.126	0.065	−0.087	0.054	−0.078	0.070	−0.078	0.042
UK->BRIC	−0.016	0.100	0.030	0.078	0.041	0.084	0.027	0.060	−0.008	0.064	−0.058	0.053	−0.031	0.057	−0.049	0.077
BRIC->USA	0.122	0.096	−0.058	0.067	−0.153	0.079	−0.069	0.065	0.009	0.062	0.009	0.054	−0.064	0.069	−0.144	0.041
USA->BRIC	−0.139	0.102	−0.161	0.073	−0.059	0.076	0.030	0.062	−0.133	0.058	−0.120	0.063	−0.071	0.069	−0.147	0.042
Developed markets index																
DEVMI->Canada	−0.152	0.085	−0.097	0.073	−0.179	0.070	−0.210	0.066	−0.140	0.060	−0.151	0.061	−0.057	0.068	−0.146	0.037
Canada->DEVMI	−0.193	0.087	−0.166	0.073	0.011	0.068	−0.146	0.062	−0.050	0.054	−0.079	0.058	0.004	0.065	−0.147	0.040
DEVMI->India	0.022	0.091	−0.013	0.072	−0.162	0.070	−0.144	0.060	−0.053	0.055	−0.035	0.058	−0.070	0.073	−0.147	0.041
India->DEVMI	−0.007	0.088	−0.187	0.073	−0.075	0.065	0.025	0.066	−0.006	0.058	−0.153	0.060	−0.011	0.052	−0.148	0.040
DEVMI->Indonesia	−0.057	0.093	−0.188	0.071	−0.085	0.077	−0.219	0.061	−0.196	0.058	0.029	0.050	−0.015	0.068	−0.145	0.037
Indonesia->DEVMI	0.017	0.080	−0.135	0.069	0.078	0.073	−0.048	0.063	−0.180	0.058	−0.072	0.071	−0.050	0.052	−0.151	0.041
DEVMI->Italy	−0.085	0.085	0.124	0.083	−0.165	0.068	−0.260	0.066	−0.217	0.055	−0.028	0.057	−0.019	0.069	−0.129	0.043
Italy->DEVMI	−0.190	0.091	0.004	0.068	−0.089	0.074	−0.193	0.064	−0.014	0.054	−0.124	0.083	−0.111	0.059	−0.086	0.079
DEVMI->Malaysia	−0.015	0.095	−0.119	0.073	−0.045	0.075	−0.101	0.061	−0.105	0.061	−0.005	0.057	−0.067	0.072	−0.022	0.043
Malaysia->DEVMI	0.001	0.091	−0.194	0.072	0.114	0.072	−0.096	0.060	−0.058	0.056	−0.126	0.066	−0.058	0.070	−0.010	0.069
DEVMI->Pakistan	−0.090	0.093	0.117	0.074	−0.032	0.071	−0.248	0.063	−0.228	0.051	−0.004	0.052	0.030	0.065	−0.147	0.040
Pakistan->DEVMI	−0.163	0.102	−0.056	0.069	0.056	0.066	−0.162	0.065	0.018	0.059	−0.094	0.060	−0.073	0.073	−0.151	0.039
DEVMI->Qatar	0.018	0.086	−0.206	0.068	−0.070	0.061	−0.114	0.059	−0.155	0.061	0.014	0.060	0.004	0.070	−0.122	0.039
Qatar->DEVMI	−0.079	0.084	−0.208	0.065	−0.190	0.071	−0.203	0.063	−0.092	0.056	−0.148	0.073	−0.045	0.067	−0.083	0.077
DEVMI->UK	−0.080	0.090	−0.043	0.078	−0.182	0.080	−0.104	0.057	−0.025	0.064	−0.043	0.050	−0.050	0.074	−0.085	0.041
UK->DEVMI	−0.144	0.090	0.018	0.074	−0.016	0.068	−0.046	0.056	−0.029	0.063	−0.032	0.062	−0.057	0.062	−0.049	0.080

Table 2: Continued.

	Composite		IMF.1		IMF.2		IMF.3		IMF.4		IMF.5		IMF.6		Residual	
	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se
DEVMI->USA	−0.067	0.091	−0.123	0.067	−0.114	0.077	0.014	0.066	−0.113	0.063	−0.071	0.054	−0.063	0.068	−0.148	0.038
USA->DEVMI	−0.177	0.090	−0.134	0.069	0.160	0.068	0.001	0.060	0.012	0.056	−0.055	0.061	−0.064	0.067	−0.148	0.039
Emerging markets index																
EMGMI->Canada	0.062	0.092	−0.176	0.068	−0.103	0.072	−0.121	0.060	−0.163	0.068	−0.127	0.069	−0.009	0.069	−0.147	0.039
Canada->EMGMI	−0.100	0.096	−0.183	0.081	0.061	0.073	−0.184	0.059	0.040	0.060	−0.034	0.052	−0.026	0.066	−0.145	0.041
EMGMI->India	0.126	0.093	−0.067	0.068	−0.027	0.068	0.015	0.062	−0.062	0.069	−0.050	0.071	−0.029	0.066	−0.141	0.040
India->EMGMI	−0.020	0.090	0.009	0.070	0.045	0.068	0.020	0.070	0.008	0.063	−0.052	0.051	−0.061	0.049	−0.147	0.037
EMGMI->Indonesia	0.007	0.093	−0.067	0.075	−0.025	0.073	−0.149	0.065	−0.224	0.066	−0.107	0.068	−0.042	0.065	−0.150	0.037
Indonesia->EMGMI	−0.029	0.094	0.010	0.079	−0.020	0.073	0.016	0.071	−0.041	0.058	−0.034	0.067	−0.060	0.053	−0.146	0.038
EMGMI->Italy	−0.070	0.094	−0.097	0.077	−0.129	0.080	−0.247	0.063	−0.173	0.060	−0.026	0.068	−0.040	0.066	−0.120	0.044
Italy->EMGMI	0.077	0.090	−0.041	0.077	−0.087	0.080	−0.194	0.069	0.075	0.057	−0.020	0.078	−0.022	0.062	−0.085	0.079
EMGMI->Malaysia	0.126	0.100	−0.056	0.077	−0.117	0.074	−0.017	0.060	−0.135	0.062	−0.077	0.068	−0.060	0.065	−0.016	0.039
Malaysia->EMGMI	0.094	0.091	−0.117	0.080	−0.068	0.078	−0.148	0.062	−0.084	0.057	−0.024	0.058	−0.065	0.072	−0.012	0.064
EMGMI->Pakistan	0.016	0.090	0.048	0.063	−0.066	0.073	−0.229	0.070	−0.206	0.060	−0.072	0.069	−0.094	0.063	−0.147	0.040
Pakistan->EMGMI	−0.098	0.097	−0.140	0.083	−0.024	0.077	−0.141	0.067	−0.088	0.060	−0.022	0.060	−0.018	0.067	−0.144	0.039
EMGMI->Qatar	−0.070	0.093	−0.048	0.072	0.034	0.070	−0.093	0.066	−0.076	0.057	−0.063	0.073	−0.018	0.069	−0.121	0.041
Qatar->EMGMI	−0.120	0.093	−0.134	0.079	−0.132	0.079	−0.210	0.061	−0.067	0.061	−0.061	0.070	−0.019	0.069	−0.079	0.078
EMGMI->UK	0.023	0.092	−0.058	0.077	−0.076	0.076	−0.140	0.061	−0.126	0.065	−0.049	0.076	−0.052	0.072	−0.086	0.039
UK->EMGMI	−0.036	0.098	0.143	0.080	0.022	0.078	−0.111	0.064	−0.018	0.062	−0.072	0.057	−0.069	0.056	−0.048	0.080
EMGMI->USA	0.027	0.093	−0.174	0.069	−0.112	0.079	0.020	0.058	−0.074	0.063	−0.071	0.071	−0.022	0.061	−0.144	0.041
USA->EMGMI	−0.102	0.092	−0.037	0.072	−0.061	0.075	−0.150	0.060	−0.117	0.059	−0.005	0.060	−0.045	0.069	−0.144	0.040
Europe markets index																
EURMI->Canada	−0.021	0.097	−0.060	0.069	−0.079	0.071	−0.130	0.062	−0.065	0.060	−0.088	0.074	−0.070	0.065	−0.080	0.079
Canada->EURMI	−0.085	0.104	−0.052	0.078	0.033	0.074	−0.268	0.061	−0.070	0.058	0.025	0.055	0.014	0.065	−0.112	0.039
EURMI->India	0.071	0.093	−0.034	0.074	−0.158	0.076	−0.054	0.062	−0.093	0.052	−0.133	0.069	−0.078	0.068	−0.085	0.078
India->EURMI	0.024	0.091	0.004	0.072	0.033	0.075	−0.075	0.067	−0.001	0.063	−0.025	0.052	−0.028	0.050	−0.125	0.038
EURMI->Indonesia	−0.045	0.093	−0.026	0.077	−0.084	0.076	−0.115	0.062	−0.160	0.046	−0.090	0.068	−0.037	0.069	−0.082	0.078
Indonesia->EURMI	−0.017	0.095	−0.008	0.073	−0.101	0.075	−0.001	0.068	−0.036	0.057	0.036	0.062	−0.064	0.059	−0.127	0.040
EURMI->Italy	−0.015	0.093	0.121	0.073	−0.147	0.078	−0.053	0.061	−0.142	0.059	0.198	0.063	−0.033	0.062	−0.125	0.078
Italy->EURMI	−0.010	0.094	−0.040	0.073	0.072	0.077	−0.158	0.065	−0.007	0.056	0.179	0.075	0.068	0.069	−0.113	0.077

Table 2: Continued.

	Composite		IMF.1		IMF.2		IMF.3		IMF.4		IMF.5		IMF.6		Residual	
	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se	ete	se
EURMI->Malaysia	0.140	0.096	−0.116	0.077	−0.062	0.071	−0.069	0.063	−0.224	0.056	−0.131	0.077	−0.077	0.070	−0.028	0.079
Malaysia->EURMI	0.103	0.097	−0.038	0.078	0.187	0.073	−0.065	0.061	−0.233	0.056	0.014	0.059	−0.065	0.061	−0.020	0.067
EURMI->Pakistan	−0.072	0.098	0.000	0.075	−0.224	0.078	−0.107	0.065	−0.151	0.057	−0.063	0.073	−0.088	0.067	−0.084	0.080
Pakistan->EURMI	−0.121	0.093	0.113	0.079	0.044	0.072	−0.024	0.074	0.066	0.057	−0.026	0.058	0.198	0.070	−0.124	0.043
EURMI->Qatar	0.121	0.096	−0.061	0.071	−0.023	0.070	−0.037	0.060	−0.073	0.053	−0.063	0.070	−0.055	0.065	−0.128	0.074
Qatar->EURMI	−0.131	0.097	−0.169	0.072	−0.102	0.080	−0.018	0.058	−0.171	0.057	0.015	0.069	−0.074	0.066	−0.123	0.079
EURMI->UK	0.029	0.105	−0.053	0.075	−0.125	0.076	−0.005	0.059	−0.005	0.058	−0.053	0.074	−0.086	0.066	−0.109	0.081
UK->EURMI	0.076	0.102	0.070	0.068	0.182	0.078	−0.089	0.058	−0.030	0.058	−0.061	0.053	−0.022	0.060	−0.124	0.078
EURMI->USA	−0.008	0.093	−0.145	0.074	−0.146	0.078	−0.042	0.062	−0.143	0.063	−0.024	0.074	−0.064	0.068	−0.080	0.076
USA->EURMI	−0.108	0.093	−0.177	0.070	−0.130	0.078	−0.117	0.057	−0.211	0.056	0.011	0.057	−0.071	0.059	−0.120	0.043
Global market Comp. Index																
GLOBALMI->Canada	0.098	0.085	−0.056	0.078	−0.006	0.080	−0.031	0.060	−0.143	0.060	−0.226	0.058	−0.063	0.055	−0.004	0.066
Canada->GLOBALMI	−0.023	0.085	−0.144	0.076	−0.072	0.074	−0.160	0.060	−0.043	0.058	−0.040	0.056	−0.044	0.074	−0.116	0.053
GLOBALMI->India	0.146	0.099	0.059	0.075	−0.170	0.079	−0.120	0.062	−0.043	0.066	−0.073	0.052	−0.037	0.060	−0.010	0.068
India->GLOBALMI	0.093	0.092	−0.072	0.074	−0.127	0.076	−0.142	0.063	0.015	0.059	−0.070	0.055	−0.050	0.058	−0.116	0.044
GLOBALMI->Indonesia	−0.216	0.087	−0.102	0.075	−0.035	0.076	−0.213	0.063	−0.234	0.062	−0.028	0.060	−0.023	0.060	−0.008	0.066
Indonesia->GLOBALMI	−0.032	0.094	−0.049	0.075	−0.033	0.075	−0.057	0.063	0.063	0.061	−0.147	0.070	−0.048	0.056	−0.114	0.044
GLOBALMI->Italy	0.036	0.094	0.012	0.076	−0.104	0.077	−0.150	0.060	−0.169	0.067	−0.018	0.055	−0.066	0.061	−0.027	0.059
Italy->GLOBALMI	0.200	0.092	−0.029	0.067	−0.028	0.082	−0.214	0.063	0.147	0.058	−0.068	0.086	−0.041	0.066	−0.116	0.081
GLOBALMI->Malaysia	−0.078	0.098	−0.005	0.078	0.028	0.080	−0.036	0.057	−0.048	0.058	−0.069	0.059	−0.015	0.061	−0.018	0.071
Malaysia->GLOBALMI	−0.099	0.090	0.159	0.081	0.004	0.080	−0.118	0.058	−0.081	0.056	−0.070	0.065	−0.020	0.066	−0.101	0.062
GLOBALMI->Pakistan	0.047	0.091	0.029	0.071	0.040	0.075	−0.177	0.061	−0.206	0.059	−0.011	0.049	−0.058	0.058	−0.008	0.066
Pakistan->GLOBALMI	0.109	0.089	−0.042	0.075	−0.005	0.083	−0.162	0.068	−0.004	0.057	−0.103	0.059	−0.054	0.071	−0.118	0.046
GLOBALMI->Qatar	0.037	0.097	0.023	0.071	0.060	0.073	−0.216	0.062	−0.147	0.060	−0.033	0.060	−0.065	0.060	−0.019	0.067
Qatar->GLOBALMI	0.026	0.092	−0.096	0.075	−0.268	0.087	−0.233	0.056	−0.134	0.053	−0.145	0.078	−0.039	0.074	−0.115	0.086
GLOBALMI->UK	0.050	0.081	0.011	0.076	−0.055	0.086	0.010	0.060	−0.125	0.059	−0.061	0.058	−0.080	0.056	−0.024	0.067
UK->GLOBALMI	0.083	0.089	0.032	0.071	−0.057	0.077	−0.076	0.064	−0.006	0.060	−0.033	0.064	−0.001	0.062	−0.114	0.081
GLOBALMI->USA	0.105	0.089	−0.133	0.070	−0.110	0.080	−0.003	0.060	−0.084	0.061	−0.127	0.054	−0.064	0.058	−0.010	0.070
USA->GLOBALMI	−0.088	0.092	0.031	0.072	−0.044	0.081	−0.041	0.054	−0.115	0.059	−0.105	0.055	−0.057	0.068	−0.124	0.046

Notes: ete = effective transfer entropy; se = standard error.

Table 3: Summary of flight-to-quality and flight-from-quality prospects between global equities and Islamic and conventional bonds.

Data series	Time scale	Market	Flight-to-quality (stocks to bonds)		Flight-from-quality (bonds to stocks)	
			Potential?	Applicable countries	Potential?	Applicable countries
Composite	—	BRIC	No	—	Yes	Canada and Italy
		DEVMI	Yes	Canada	Yes	Canada, Italy, and the USA
		EMGMI	No	—	No	—
		EURMI	No	—	No	—
		GLOBALMI	Yes	Indonesia	No	—
IMF.1	Short term	BRIC	Yes	Canada, Italy	Yes	Canada, Malaysia, and the USA
		DEVMI	Yes	Indonesia, Malaysia, Qatar, and the USA	Yes	Canada, India, Indonesia, Malaysia, Qatar, and the USA
		EMGMI	Yes	Canada and the USA	Yes	Canada, Qatar, and Pakistan
		EURMI		USA	Yes	Qatar and the USA
		GLOBALMI	Yes	USA	Yes	Canada
IMF.2	Short term	BRIC	Yes	Canada, Italy, and the USA	Yes	Qatar
		DEVMI	Yes	Canada, India, Italy, and the UK	Yes	Qatar
		EMGMI	No	—	Yes	Qatar
		EURMI	Yes	India, Italy, Pakistan, the UK, and the USA	Yes	USA
		GLOBALMI	Yes	India	Yes	India and Qatar
IMF.3	Short term	BRIC	Yes	Canada, Indonesia, and the UK	Yes	Qatar
		DEVMI	Yes	Canada, India, Indonesia, Italy, Malaysia, Pakistan, Qatar, and the UK	Yes	Canada, Italy, Pakistan, and Qatar
		EMGMI	Yes	Canada, Indonesia, Italy, Pakistan, the UK, and the USA	Yes	Canada, Italy, Malaysia, Pakistan, Qatar, the UK, and the USA
		EURMI	Yes	Canada and Indonesia	Yes	Canada, Italy, and the USA
		GLOBALMI	Yes	India, Indonesia, Italy, Pakistan, and Qatar	Yes	Canada, India, Italy, Malaysia, Pakistan, and Qatar
IMF.4	Midterm	BRIC	Yes	Indonesia, Malaysia, Pakistan, and the UK	Yes	Canada and the USA
		DEVMI	Yes	Canada, Indonesia, Italy, Malaysia, Pakistan, Qatar, and the USA	Yes	Indonesia
		EMGMI	Yes	Canada, Indonesia, Italy, Malaysia, Pakistan, and the UK	Yes	USA
		EURMI	Yes	India, Indonesia, Italy, Malaysia, Pakistan, Qatar, and the USA	Yes	Malaysia, Qatar, and the USA
		GLOBALMI	Yes	Canada, Indonesia, Italy, Pakistan, Qatar, and the UK	Yes	Qatar and the USA
IMF.5	Midterm	BRIC	Yes	Indonesia	Yes	India, Italy, Malaysia, Pakistan, and the USA
		DEVMI	Yes	Canada	Yes	India, Malaysia, and Qatar
		EMGMI	Yes	Canada	No	—
		EURMI	Yes	India and Malaysia	No	—
		GLOBALMI	Yes	Canada and the USA	Yes	Indonesia, Pakistan, Qatar, and the USA
IMF.6	Midterm	BRIC	No	—	No	—
		DEVMI	No	—	Yes	Italy
		EMGMI	No	—	No	—
		EURMI	No	—	No	—
		GLOBALMI	No	—	No	—
Residual	Long term	BRIC	Yes	Canada, India, Indonesia, Italy, Pakistan, Qatar, the UK, and the USA	Yes	Canada, India, Indonesia, Pakistan, and the USA
		DEVMI	Yes	Canada, India, Indonesia, Italy, Pakistan, Qatar, the UK, and the USA	Yes	Canada, India, Indonesia, Pakistan, and the USA
		EMGMI	Yes	Canada, India, Indonesia, Italy, Pakistan, Qatar, the UK, and the USA	Yes	Canada, India, Indonesia, Pakistan, and the USA
		EURMI	Yes	Qatar	Yes	Canada, India, Indonesia, Italy, Pakistan, and the USA
		GLOBALMI	No	—	Yes	Canada, India, Indonesia, Pakistan, and the USA

This observation rekindles Baur and Lucey's [8] flights phenomenon. Specifically, at the frequency-domain space, we find that from IMF.1, Islamic and conventional bonds mostly respond negatively to information flow from the global equities markets. Italy and Canada are significant negative recipients of information from BRIC equities, meaning that investors of BRIC equities could attain safe haven opportunities [11] from Canadian and Italian bonds. When there are shocks from the bond markets to BRIC equities, BRIC equities could offer a hedge to bonds from Canada, Malaysia, and the USA only.

For developed equities markets (DEVMI), bonds from Qatar, Indonesia, the USA, and Malaysia could provide safety nets since they are significant negative recipients of shocks from developed markets' equities. Similarly, the returns on developed markets' equities could offer a hedge against shocks to bond yields from Canada, India, Indonesia, Malaysia, Qatar, and the USA. Notably, the Canadian and American bonds only could offer safety nets to equities from emerging markets (EMGMI) and in times of shocks to Islamic and conventional bonds, emerging markets' equities could be safe assets for bonds in Canada, Qatar, and Pakistan only. The only bond market that could safely sustain losses to developed (DEVMI) and European (EURMI) markets equities is that of the USA. When shocks are experienced by the bond market in Canada (Qatar and the USA), European (Global–GLOBALMI) equities could hedge against such shocks. These observations are reflective of flights-to-quality (FTQ) and flight-from-quality (FFQ), as Baur and Lucey [8] describe. Safe havens, hedges, and diversification prospects for the bond and equities markets in times of pandemic are brought to bear by our findings.

At IMF.2 (see Figure 5), we find several FTQ possibilities for equity investors in BRIC equities markets using bonds from Canada, Italy, and the USA; for the developed markets equities investors, bonds from Canada, India, Italy, and the UK; for the European markets equities, bonds from India, Italy, Pakistan, the UK, and the USA; for global market equities, bonds from India only. No FTQ possibility was revealed for emerging markets equities investors. Conversely, in times of shocks to the bond markets, the Qatari bond only could attain a hedge from all equities markets except the European bond, which rather offers safety nets to the American bonds. Global equities could also offer safety nets to Indian bonds when the Indian bond market receives shocks.

Nearing the end (start) of the short (medium) term, that is, at IMFs 3 and 4, FTQ and FFQ opportunities are available to almost all global equities and bond investors, respectively, with Indonesian bonds emerging as a predominant safe haven asset for all global equities. Similar observations are made at IMF.5, which falls within the intermediate term. It is worthy to note that shocks presented to the studied Islamic and conventional bond markets cannot be hedged by the European and emerging equities. Also, the Canadian, Indian, Indonesian, Malaysian, and American bond markets only can provide safety nets to specific global equities in the intermediate term. Thus, FTQ and FFQ opportunities are somewhat limited in the intermediate term of the COVID-19 pandemic. Within the intermediate term, the stock markets might have acquired some level of information concerning the pandemic and, hence, might not respond to shocks as they did in the early periods of the pandemic [6].

In the long term, represented by the IMF Residual, we find FTQ and FFQ prospects presented to most bond and equities investors, respectively, across all market blocs with the global equities market being an exception. Specifically, in line with the "flights" literature [8–13], we find consistent FTQ opportunities for equities investors in BRIC, developed, emerging, and European markets using bonds from Canada, India, Indonesia, Italy, Pakistan, Qatar, the UK, and the USA. No such opportunity exists for investors of global market equities. Conversely, there exist FFQ opportunities for bond investors in Canada, India, Indonesia, Pakistan, and the USA, when these markets experience shocks. The returns on these bond yields could be hedged against using equities from all five market blocs. Such an FFQ opportunity exists for bond investors in Italy but they could use European equities only to hedge against losses on their bond yield returns.

In totality, the ETEs between bonds and global equities at the frequency-domain level vary in direction and significance across all time horizons. This observation substantiates our choice of analysis, which is the frequency-domain analysis, as against analysis at the composite level. This reiterates the homogeneous and adaptive market hypotheses of Müller et al. [34] and Lo [33], respectively. In addition, we could deduce that the time-varying nature of the ETEs suggests that investors would intensify their search for safe assets during these periods and this corroborates the CMH of Owusu Junior et al. [6]. These observations, however, refute the operability of the efficient market hypothesis of Fama [27, 28]. A summary of the FTQ and FFQ prospects is provided in Table 3.

6. Practical Implications

In sum, the fact that flights occur during times of market tumult is excellent news for market participants since it indicates that there is one asset or asset class for which prices surge during times of market turmoil. We demonstrate empirically that flights may improve the financial system's stability and robustness by allowing diversity to be effective when it is most required. The findings have financial and portfolio implications for investors who are considering how to deploy their investments. Notable practical implications are drawn from our study.

Through the analysis at multiscale, represented by IMFs 1–6 and the residual, our findings divulge that institutional investors stand a chance to benefit from conventional and Islamic stocks and bonds during market shocks, specifically the COVID-19 pandemic. When shocks befall bond markets, our findings suggest that institutional investors could mitigate losses by channeling investible funds to either Islamic or conventional stocks. Likewise, when shocks befall either stock market, institutional investors could mitigate losses by flocking to quality earnings offered by the bond markets.

Generally, the findings corroborate the flights (FTQ and FFQ) phenomena, and such opportunities are consistent—with a few exceptions—across all investment horizons, represented by IMFs and the residual. For speculators and hedgers, our findings divulge that both conventional and Islamic stocks and bonds could be reliable assets of trade in all investment periods. Portfolios consisting of either Islamic or conventional bonds and global equities need to be regularly monitored during crisis periods since the relative diversification benefits may lose their significance across different investment horizons.

7. Conclusions

This study employed a data-driven technique, the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN)-based entropy, to assess information flow between global equities and bonds from both Islamic and conventional markets. We use a longer sample period, from January 02, 2020, to September 08, 2021, yielding 264 data points. Our data set covers the daily 10-Year bond yield indices of 5 key Islamic and G4 markets, as well as daily global equity indices for 5 market blocs (BRIC, developed markets index, emerging markets index, Europe Index, and global market composite index). The large data set is necessary to better understand the complexities in investor behaviour among Islamic and conventional markets during the COVID-19 pandemic. Two main stages were followed to process the data set.

First, the ICEEMDAN approach was used to decompose the return series of the 9 bond yield markets and 5 global equity indices into intrinsic periods, which represent the short-, intermediate-, and long-term horizons. This aided in understanding the dynamic nature of investors' responses to the pandemic whilst also reducing noise in the series. This method supports the CMH, HMH, and AMH, all of which are opposed to the EMH. Second, the Rényi transfer entropy (RTE) was used on composite series and their accompanying frequency domains to measure information flow between the bond and equities markets. A fault weight of 0.30 was specified to cater for tailed observations in bond yield and stock returns. In the context of the COVID-19 pandemic, Rényi transfer entropy accommodates for fat tails in equity returns while discriminating between high risk (negative ETEs) and low risk (positive ETEs) equities.

Across all time horizons (short, intermediate, and long run), the findings largely support the AMH [33], the HMH [34], and the CMH [6], all of which are anti-EMH. Corollary to our findings, there is insufficient empirical evidence to retain the null hypothesis that "there exists no significant information flow between the studied global equities and the Islamic and conventional bond yield markets."

Overall, the findings suggest that in response to market dynamics, investors modify their mood, risk, and reward preferences across time to fulfil their portfolio objectives. Specifically, we note that during turbulent market periods, the frequency at which investors rebalance their portfolio holdings heightens, which is as a result of their search for assets that would provide safety nets for their existing portfolios. This rekindles the fundamental problem of portfolio diversification, in line with the portfolio allocation problem [32]—the overriding portfolio objectives—of maximising (minimising) returns (risks). The dynamism in transfer entropies revealed in the study suggests that investors would increase their search for assets that would act as safe havens, hedges, or diversifiers [11] during the COVID-19 era.

From the ETEs, we present that the intensified search for safety assets in the COVID-19 pandemic results in the creation of markets, which vary across time scales, allowing investors to both adapt and adjust their risk and return preferences over the crisis period. These findings substantiate the adaptive and heterogeneous market hypotheses, the AMH [33] and HMH [34], respectively, putting the study in context vis-à-vis the methodology applied. Furthermore, the study corroborates the hypothesis of competitive markets, the CMH, postulated by Owusu Junior et al. [6]. The reinforcement of the CMH by our findings is such that information flow and spillovers across assets and/or asset classes intensify during turbulent market periods (like the COVID-19 pandemic presents) owing to rational, though irrational investors' never-ending quest for rival returns and risks to meet overriding portfolio objectives [32]. The ETEs offer support for this supposition and hence, it is not surprising for equities investors to rush into bond markets during tempestuous trading periods, which the COVID-19 pandemic is no exception, per our results.

More importantly, the flow of information between stocks and bonds presents several "flight" opportunities [7, 8, 36] for Islamic and conventional investors. Our findings suggest that both Islamic and conventional bonds could offer safety nets to international equities investors during the COVID-19 pandemic across the short-, medium-, and long-term periods with little exceptions in the medium term. Within the short and medium terms, Islamic and conventional bond yield returns could act as safe havens, diversifiers, and hedges for international equities and the same could be observed for international equities. Indonesian bonds consistently act as a safe asset for global equities across the short and intermediate investment periods. Bond investors from either the Islamic or conventional (G4) markets could flock to stocks when the stock markets are hit hard by the pandemic. This results in a successful flight-to-quality, suggesting that safe or quality earnings lie in the bond markets for equity holders across diverse time scales in the crisis period. Similarly, if the bond market is hit hard by the COVID-19 pandemic, investors could achieve diversification, hedging, and safe haven using stocks across the globe. This way, investors hedge against the losses borne by their investments in bonds using stocks, and this is known as the flight-from-quality [8].

Furthermore, the findings of this research may impact policymakers' responses to changes in various asset classes, allowing them to better monitor financial markets and adjust macroeconomic policies, which are indispensable determinants of bond prices or returns. Given that market dynamics for bonds and stocks could bear some exceptions depending on the investment or trading horizon, as shown in this study with the decomposed data series, policymakers are to be wary of these contingent dynamics and respond to them by implementing dynamic policy guidelines during turbulent periods like pandemics. Bubbles in turbulent trading periods are almost likely to cause unexpected interrelations between macroeconomic variables like interest rates, exchange rates, etc., which affect financial markets including stocks and bonds. Thus, dynamic and proactive policy measures are required of policymakers to ensure that fundamental market dynamics are not significantly impacted during Black Swan periods. Lucrative equities and bond markets could attract significant capital flows to economies and hence, their effective regulation serves as an essential policy measure for boosting the potency of financial markets whilst fostering economic growth.

Future studies could investigate information flows between specific stock markets rather than aggregated indices for market blocs. The flow of information between the determinants of bonds and stock prices or returns could be considered in future studies.

Data Availability

The bond yield and equities indices data provided by EquityRT to support the conclusions of this research are under license and so cannot be made publicly accessible.

Conflicts of Interest

The authors disclose that they do not have any conflicts of interest.

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