Multi-frequency information transmission among constituents and global equity returns: a sustainable and conventional way of investing

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Abstract

Purpose – This study investigates information flow of market constituents and global indices at multi-frequencies.

Design/methodology/approach – The study's findings were obtained using the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (I-CEEMDAN)-based cluster analysis executed for Rényi effective transfer entropy (RETE).

Findings – The authors find that significant negative information flows among sustainability equities (SEs) and conventional equities (CEs) at most multi-frequencies, which exacerbates diversification benefits. The information flows are mostly bi-directional, highlighting the importance of stock markets' constituents and their global indices in portfolio construction.

Research limitations/implications – The authors advocate that both SE and CE markets are mostly heterogeneous, revealing some levels of markets inefficiencies.

Originality/value – The empirical literature on CEs is replete with several dynamics, revealing their returns behaviour for diversification purposes, leaving very little to know about the returns behaviour of SE. Wherein, an avalanche of several initiatives on Corporate Social Responsibility (CSR) enjoin firms to operate socially responsible, but investors need to have a clear reason to remain sustainable into the foreseeable future period. Accordingly, the humble desire of investors is the formation of a well-diversified portfolio and would highly demand stocks to the extent that they form a reliable portfolio, especially, amid SEs and/or CEs.

Keywords Entropy, Mutual information, Decomposition, Sustainable responsible investing, Frequency-dependent

Paper type Research paper

1. Introduction

The idea and tenets of SRI have gained prominence and have taken over new investors' management funds around the world (Townsend, 2020). Socially Responsible Investing (SRI)

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portfolios typically exceed or generate returns that are at least comparable to market performance from the standpoint of portfolio management (Berkman *et al.*, 2021). For instance, evidence indicates that when additional financial grades are used as proxies for a firm's CSR behaviour, a strategy in which investors buy the most socially responsible corporations and sell the least socially responsible companies yields positive alphas (Lins *et al.*, 2017). By doing both good and well, socially conscious investors can maximise their returns.

As opposed to using CSR ratings and business performance indicators, the construction of a market-based framework that provides a sound legal and regulatory environment has recently received priority (Levine, 2005). This is supported by the increase in financial markets' integration due to the heightened financial openness and trade liberalisation policies across the globe while ensuring richer risk management mechanisms and the forming of reliable portfolios. Therefore, the market-based system promotes economic development in the long run through the synergistic impact of a broad array of firms (Balcilar *et al.*, 2018; Asafo-Adjei *et al.*, 2021a, b). This is particularly crucial since the numerous market performance contributions made by distinct CSR-inclined firms may combine to benefit blocs at the national, regional or international levels.

As a result, nascent and fledgling bodies of literature have shown that using equity and CSR measurements is responsive (Galema *et al.*, 2008; Hayward, 2018; Dorfleitner *et al.*, 2018; Durand *et al.*, 2019; Berkman *et al.*, 2021, etc.). The results of these research showed that SRI screening greatly outperforms the numeric (Derwall *et al.*, 2005). On the other hand, Geczy *et al.* (2021) found that investors are forced to pay a premium for the funds committed to SRI stock. However, Berkman *et al.* (2021) found no statistically significant difference between the 2008 Global Financial Crisis (GFC) performances of high and low CSR-inclined enterprises, adding to the varied dynamics of sustainability equity (SE) returns across time.

Nonetheless, it is not overwhelming to advocate that the upsurge in the share of SRI funds plays a significant role in ushering inducements towards an incessant elevation of SR standards to a degree that their performance is not steadily inferior to other funds (Consolandi *et al.*, 2009). This is a result of the topical diffusion of SRI equities to provide fresh intuitions into the SR standards on corporate equity's performance.

In order to combine global reach with local knowledge, the study uses the Standard & Poor's (S&P) Dow Jones sustainability equity indices, which debuted in 1999. Through collaboration with exchanges throughout the world, these indices were created for both the domestic and global investment communities (Naqvi and Jus, 2019a). The sustainability indices include, but are not limited to the World Index, the USA, North America, Emerging, Europe, Frontier and Sharia, covering a broad array of global and regional blocs.

The Dow Jones Sustainability Index (DJSI) has a tremendous market influence and a promising future for the sustainability investing sector (Naqvi and Jus, 2019b; Townsend, 2020). Over 37,000 sustainable indicators were accessible globally as of 2019 (Naqvi and Jus, 2019a). Some initiatives, including the United Nations (UN) Sustainable Development Goals in 2015, which urge most businesses worldwide to have a crucial mandate to operate sustainably, help to support this (Naqvi and Jus, 2019a).

The DJSI World as a possible proxy for the global sustainability index is made up of premier environmental performers regarding a benchmark of the 1st 10% of industry performers (Fundamental Rights Report, 2016; Durand *et al.*, 2019). This induces competition for firms keen to be included, continued or expunged from the index. Accordingly, the strength of information flows among the markets of similar or differing asset classes are intensified by irrational investors' persistent search for competing risks and returns to meet their portfolio goals to accentuate the competitive market hypothesis (CMH) of Owusu Junior *et al.* (2021b).

Despite the expanding corpus of literature on SEs, there is still a lack of knowledge addressing the structure of returns from sustainable investments and information flows across different investment horizons (Consolandi *et al.*, 2009; Hawn *et al.*, 2018; Hayward, 2018; Durand *et al.*, 2019; Helliar *et al.*, 2022). As a result, the study examines the return behaviour of sustainability-related stocks in relation to the degree of information flow across the stocks across investment horizons. This is important to consider when evaluating risk management choices, portfolio diversification and the distribution of government rules and policy decisions regarding sustainable equities.

Existing literature has not yet utilised multi-frequency techniques to respond to information flow among SEs amid conventional equities (CEs). The techniques are the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (I-CEEMDAN)-based cluster analysis and entropy. Although a plethora of literature has utilised most of these techniques on several other financial assets (Zhu *et al.*, 2015; Adam *et al.*, 2022; Owusu Junior *et al.*, 2021b; Gyamfi *et al.*, 2021; Asafo-Adjei *et al.*, 2022a etc.), limited attention has been extended to SE returns.

The I-CEEMDAN is a viable approach for sampling, dealing with signal noise and greatly reducing the frequency aliasing problem that can arise with EMD, EEMD and CEEMDAN, as respectively proposed by Huang *et al.* (1998), Wu and Huang (2009) and Torres *et al.* (2011). The I-CEEMDAN decomposes input signals into main modes. The modes are termed as intrinsic mode functions (IMFs). The IMFs depict – short-, medium- and long-term horizons which are considered in this current study to respond to information flow.

Additionally, the transfer entropy measures the reduction in uncertainty, particularly, when forecasting variables are conditioned on past values and thus makes it easier to model statistical causality between financial time series (Adam, 2020; Benthall, 2019). To account for tail events which are ideal for revealing stressed markets outcomes (Asafo-Adjei *et al.*, 2022a), the Rényi transfer entropy is applied in this study.

The employed methodologies help to capture multi-frequency information flow between equity returns better for investing decisions. For instance, it would enable investors to observe the degree of extensive propagation of shocks among assets at various investment horizons (short, medium and long terms) where the knowledge of one asset, possibly, indicates considerably more uncertainty than knowing the history of only the other asset. Accordingly, investors are able to minimise their portfolio risks and earn better returns at certain investment horizons depicted at by the multi-frequencies coupled with a negative information transfer (Boateng *et al.*, 2022; Bossman *et al.*, 2022a). This is in response of the heterogeneous, competitive and adaptive behaviours of markets in line with the behavioural market hypothesis where markets' participants are irrational across investment horizons, which makes them state-dependent.

We contribute to the literature in the following ways. First, we form a portfolio among sustainable equities amid CEs. Second, the I-CEEMDAN-based cluster analysis is utilised in this study to effectively reduce noise from the data and form a reconstructed series of high , medium and low frequencies in addition to the residue. This approach is relevant to capturing information at diverse investment horizons while maintaining, to a large extent, the delayed responses of prices to information relative to the individual IMFs, which might not provide sufficient returns behaviour. Accordingly, in this study, we combine similar IMFs by observing the mean periods of the equity returns obtained through cluster analysis. Third, we investigate information flows among SEs amid CEs with the aid of the Rényi transfer entropy, which allows enquiries of financial time series at low probability events. Low probability events are mostly preferred by assigning higher weights to the lower tails since most financial time series are prone to dropdowns.

The remaining sections are arranged in the following ways. We present the methodology required to achieve the purpose of this study in section 2. Section 3 has the results and discussion of the study whereas section 4 concludes the study.

2. Literature review

Information flow is defined by diverse academic disciplines; however, most definitions of information flows in the natural sciences are built on the foundational work of Shannon (1948) with several other applications, including physics (Edet and Ikot, 2021; Jaynes, 1957; etc.), biology (Mikhailovsky, 2021; Skinner and Dunkel, 2021) and finance (Asafo-Adjei *et al.*, 2022a; Bossman *et al.*, 2022a; Adam, 2020; Agyei *et al.*, 2022d; Asafo-Adjei *et al.*, 2022e; Boateng *et al.*, 2022; Bossman *et al.*, 2022b; Qabhobho *et al.*, 2022; etc.). Information is transmitted among entities in two ways: first, a classification by abstract states and second, the degree of background linkages and regularities the entities share (Ostalé, 2020). Regularity is the state of being predictable to enhance effective decision-making. As posited by Ostalé (2020), it is not necessary to determine what the entities are, so long as they relate to each other using a classificatory relation, information flows become prominent. Moreover, Benthall (2019) avers that information flows are located in the context of causal linkages. It becomes obvious to indicate that information flow theory makes it possible to quantify the extent to which one thing carries information about another.

Outcomes provided by empirical studies divulge that reciprocal information exists owing to interconnections between variables and that one variable can learn from the behaviour of the other through observation. Information flows among variables become reliable when the information is well refined, due to surges in the number of connections (Ostalé, 2020). This can be applied in financial time series which experience rapid oscillations. As a result, decomposition-based information flows become a suitable tool to ensure a more refined noise reduction information flows between financial assets. A growing body of academic literature in finance and economics employs information flow theories due to several reasons, including the degree of similarities, integration and competitiveness occasioned by the irrational behaviour of investors across investment horizons. It becomes necessary to examine information flows among SEs that demonstrate high market performance with prospects for similar dynamics.

The current study also sheds light on the CMH of Owusu Owusu Junior *et al.* (2021b) that "in part, the intensity of information flows and spillover between markets of the same and differing asset classes are exacerbated by rational, albeit irrational investors' relentless search of competing rewards and risks to satisfy the portfolio goals" (p. 2). Consequently, there is a high expectation of information flows among SEs across diverse investment horizons (short, medium and long term) and calendar times regarding market participants' irrationality. It is blatant that the behavioural dynamics of financial markets stimulate asymmetry, nonstationary and nonlinearity escalating noise in asset returns' price-generating systems requiring a pragmatic approach to account for these complexities.

A growing body of academic literature has spearheaded the exploration of information transmissions between financial assets through the information theory. Information is transmitted among financial assets classes regarding competing risks and returns intensified by the behavioural intentions of investors across investment horizons. This has made most financial asset classes exhibit mutual information where most of these assets can observe the behaviour of others. The empirical literature on information flows is replete with information flows among financial assets such as commodities (Lahmiri and Bekiros, 2020b; Asafo-Adjei *et al.*, 2022a, b) global, regional and major world markets (Lahmiri and Bekiros, 2020a; Owusu Junior *et al.*, 2021a; Asafo-Adjei *et al.*, 2021c; Bossman, 2021; Bossman *et al.*, 2022a), cryptocurrencies (Jang *et al.*, 2019; Asafo-Adjei *et al.*, 2021c; Assaf *et al.*, 2022), etc. Findings from these studies are inconclusive and may be subjected to different structural breaks or sampled period analyses revealing diverse economic events for distinct assets classes.

Outcomes from these studies either indicate asymmetric or nonlinear bi-directional and unidirectional causality among financial assets (Jang *et al.*, 2019; Owusu Junior *et al.*, 2021b; Asafo-Adjei *et al.*, 2021c; Assaf *et al.*, 2022; Bossman *et al.*, 2022a, etc.) or reveal less significant information flows (Bossman, 2021; Asafo-Adjei *et al.*, 2022a, b; etc.). Notwithstanding, depending on the direction of causality and the market conditions, diversification, safe haven and hedging benefits become predominant for certain asset classes. Moreover, it must be noted that outcomes from these studies mostly divulge the concentration of randomness and disorder in less probable events. What is yet to be known is information flow between sustainable and conventional equities at diverse investment horizons.

It becomes arguable whether SEs emulate similar dynamics of these conventional equities at diverse investment horizons. There exist countless SEs at the individual firm, national and global levels. However, due to the increasing level of financial and economic integration among most financial assets, the study employs regional as well as global proxies of the sustainable and conventional equities to better capture the multi-frequency information flow.

As averred by Kwon and Yang (2008) and Osei and Adam (2020), information flows between stock markets occur between the entire market and its constituents as well as other financial markets. This is not overwhelming because stock markets operate in a nonisolated system, which interacts and exchanges information with the real economy. That is, individual stocks are priced depending on several factors but are not limited to available information to the entire market, information peculiar to the individual stocks as well as information from other financial assets (Osei and Adam, 2020). As a result, the study examines information flows between regional equities as constituents and global equities as the entire market. To effectively bridge the gap in prior literature on information flows, the study does not only consider information flows among the SEs but includes other conventional assets to enhance comparison.

3. Methodology

3.1 I-CEEMDAN

The I-CEEMDAN proposed by Colominas *et al.* (2014) has the best of these qualities when compared to the others. While CEEMDAN performs better than previous methods in removing noise, reconstructing the signal and determining SNR, it falls short on two counts: (1) residue noise is contained in the model and (2) spurious mode issue (Li *et al.*, 2020). The I-CEEMDAN algorithm adapted from Li *et al.* (2020) is as shown as follows.

(1) Append a white-noise $\tau_1[\omega^{(i)}]$ to a signal x to result in a new series

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

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

(2) Compute the local mean of $x^{(i)}$ using EMD and retrieving the first residual

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

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

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

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

3.2 Cluster analysis

The IMFs were classified in this work into multi-frequencies (high, medium and low frequencies) using the Cluster analysis technique. The multi-frequencies were discovered by looking at the mean periods of each IMF (Zhu *et al.*, 2015; Gyamfi *et al.*, 2021; Adam *et al.*, 2022; Asafo-Adjei *et al.*, 2022a). In this instance, the mean period was calculated using the average frequency of each IMF. According to Adam *et al.* (2022), it is determined by dividing the total number of points by the total number of peaks.

$$\frac{Total\ observations}{number\ of\ maxima} \tag{4}$$

where the extrema function is used to determine the number of maxima (peaks). Utilising knowledge from the dynamics of the mean periods, the IMFs are combined to create a rebuilt series into each of their individual multi-frequencies.

3.3 Rényi effective transfer entropy (RETE)

The Rényi transfer entropy (RTE) (1970), which indicates uncertainty inside a system, is built on the Shannon entropy (Shannon, 1948; Behrendt *et al.*, 2019). Due to the research of a probability distribution, several experiments (p_j) are carried out. According to Hartley (1928), if the average information is found, symbols take the following form:

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

where n denotes several symbols' observations regarding probabilities P_j.

The Shannon entropy shows a discrete random variable (J). According to Behrendt *et al.* (2019), the typical number of bits required for encoding independent draws at the maximum can be represented as follows:

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

Under the Markov framework, Shannon entropy took insights from the Kullback–Leibler distance concept to measure information flows amid two time series. The study considers two discrete random variables, I and J (which are the equity indices), and corresponding marginal probabilities of $P(i)$ and $P(j)$. Simply, the joint probability of the discrete variables can be seen as $P(i, j)$. It has a dynamic structure that resembles a stationary Markov process of order k (Process I) and I (process J). The Markov property implies that the probability of spotting I at time $t+1$ in state i dependent on the k prior observations is $p(i_{t+1}|i_t, \ldots, i_{t-k+1}) = p(i_{t+1}|i_t, \ldots, i_{t-k})$. In encoding the observation in $t+1$, the mean number of bits needed, given that the *ex ante* k observations are obtained, can be offered in the following form:

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

where $i_t^{(k)} = (i_t, \ldots, i_{t-k+1})$ (for process J). Under the Kullback–Leibler distance phenomenon in the context of two random variables, the flow of information from process J to process I is estimated through quantification of the deviation from the generalized Markov property $P(i_{t+1}|i_t^{(k)}) = P(i_{t+1}|i_t^{(k)}, j_t^{(I)})$. Regarding what is presented earlier, the Shannon entropy is then shown as follows:

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

where $T_{J \to I}$ estimates information flows from J to I. Harmoniously, information flows $T_{I \to J}$ can be realised as from I to J. Quantifying the differential can disclose the prevailing direction of the information flow between $T_{J \to I}$ and $T_{I \to J}$.

Following Beck and Schögl (1995), the escort distribution $\varnothing_q(j) = \frac{p^q(j)}{\sum_j p^q(j)}$ with $q > 0$ to normalise the weighted distributions is applied to emphasise the resultant RTE as

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

It should be noted that the RTE computation can reveal reversed results. As a result, knowing J record creates noticeably more doubt than knowing I record alone would. For possible diversification, this is perfect. The effective transfer entropy is determined as the transfer entropy divided by the effective sample size because the transfer entropies may be skewed in small samples (Marschinski and Kantz, 2002), as shown in equation 10:

$$ETE_{J \to I}(k,l) = T_{J \to I}(k,l) - T_{Jshuffled \to I}(k,l), \tag{10}$$

where $T_{Jshuffled \to I}(k,l)$ represents the transfer entropy using a shuffled version of the time series J; that is, through a random selection of observations from the actual time series J and adjusting them to produce a fresh time series, causing chaos for the dependencies in time series J, but not superintending the statistical reliance between J and I. Recurrent RTE estimations are used to determine the information transmission, which has a null hypothesis that there are no information flows.

3.4 Data sources and description

Daily S&P Dow Jones sustainability equity indices from Global, Africa, Asia, North America, South America, Emerging, Europe, Frontier, Shariah and other regional categories were used in the research. As a result of the increased financial market integration and capital market liberalisation within regional blocs, the study uses global and regional categorisations of sustainability equity indices (Owusu Junior *et al.*, 2021a). Asafo-Adjei *et al.* (2022b, c) further revealed high degree of similarities and integration among the selected sustainability equites due to the current trends in globalisation through liberalisation policies for a more integrated financial market. The daily S&P Dow Jones sustainability equity indices were gleaned from the RobecoSAM website.

To make comparisons easier, 10 conventional stocks are also included. Except for the NAREIT Global Real Estate Index and NASDAQ 100 Volatility Target (Global Indices), which were gleaned from yahoo finance and investing.com, respectively, the remaining indices were obatined from EquityRt. The daily data cover the period from November 12, 2012, to December 2, 2021, totalling 2,102 observations. The suggested time frame takes into account major economic events such as the aftermath of the 2008 GFC, the Eurozone crisis, trade tensions between the USA and China, the COVID-19 pandemic and so on. The sampled sustainability equity indices and conventional equities, which were chosen based on consistent data availability over the given period, are specifically shown as supplementary files (see, Table S1).

4. Results and discussion

4.1 Descriptive statistics

Figure 1 displays the prices of both sustainability and conventional equities from 2012 to 2021. It can be observed that the prices of SEs and CEs demonstrate similar dynamics across

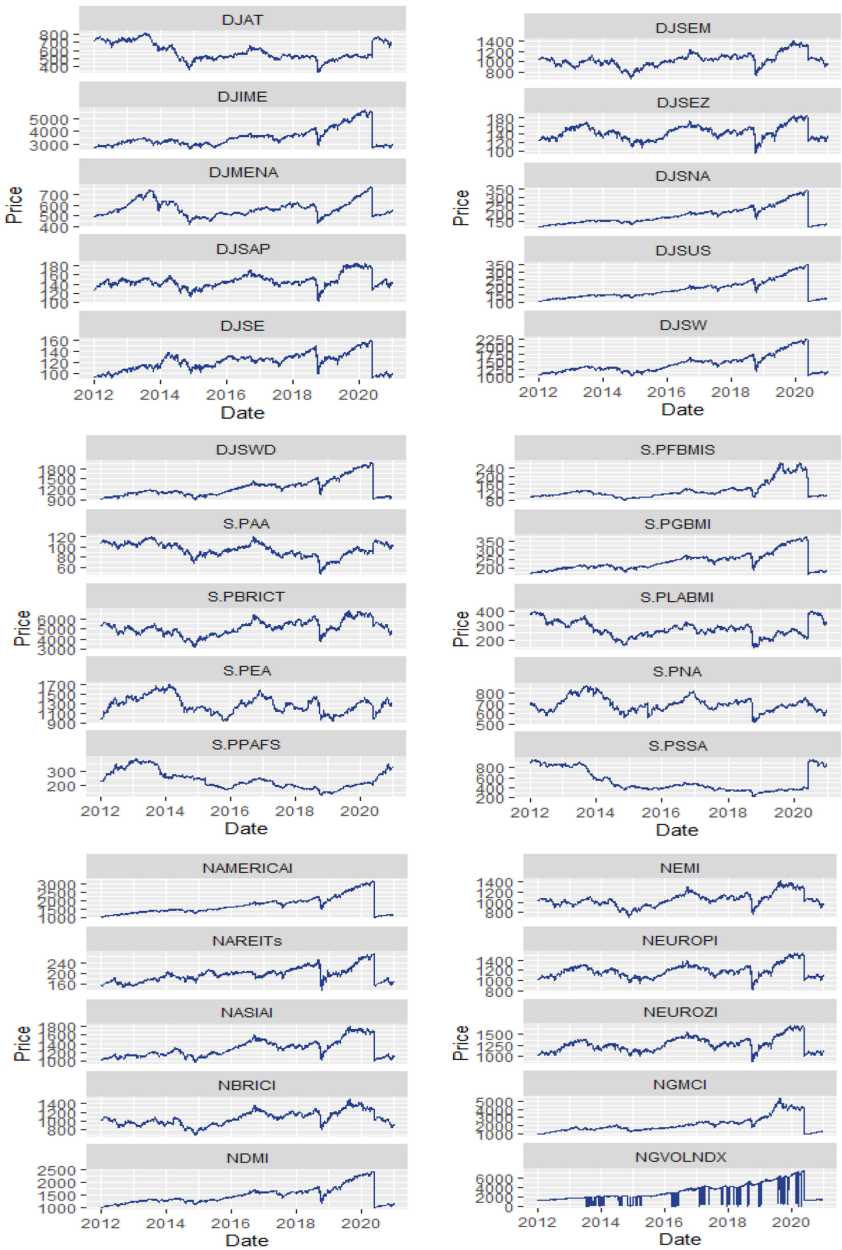


Figure 1.
Plots of price series

Source(s): Figure by authors

time. Specifically, we notice a price dip for most equities in the first quarter of 2021. This suggests the delayed responsiveness of the equities prices to shocks from the COVID-19 pandemic. We notice an interesting outcome of a plunge in prices around 2019 for almost all equities. During this period, investors fretted about a plummeting global economy. To mention a few, investors' worries emanated from disruptive trade wars, especially, the USA–China trade wars, excessive tariffs, Brexit (United Kingdom's desire to depart from the European Union), etc. This induced the IMF to downgrade its projections for global economic growth to approximately 3%, and considered the lowest estimate since the 2008 GFC.

Figure 2 presents logarithmic returns series for 20 SE returns and CE returns. As clearly shown in Figure 4, shocks in the return series are generally prominent in the early portions of 2020, suggesting the adverse impact of the COVID-19 pandemic. This highlights that SEs are not entirely insulated from severe economic shocks. The NGVOLNDX equity index on the other hand reveals chunks of excess fluctuations across time, demonstrating its relevance as a volatility measure. A glance at the DJSEZ index stipulates that the Eurozone crisis as a local regional economic shock has less impact on their average sustainability equity returns (ER) relative to the economic impact of the COVID-19 pandemic.

Seven descriptive statistics for 30 ER are shown in Table 1. Table 1 shows that ER have a poor performance and vary from −0.04% to 0.08%. All of the returned series have little variance, indicating some degree of regularity, with the exception of NGVOLNDX, whose spread is closer to 1. However, the data's distribution deviates from a normal distribution. This conclusion is quantitatively supported by the Jarque-Bera statistic for a nonnormal data distribution, which highlights negatively skewed and peaked distributions. Additionally, all of the return series are stationary according to the Kwatkowski–Phillips–Schmidt–Shin (KPSS) test, which demonstrates that the stationarity of all return series cannot be ruled out (p-value > 0.05). The initial returns series, however, appear to be nonlinear according to the Teraesvirta's neural network (TRS).

4.2 Procedures for IMF reconstruction into their multi-frequencies

Following the research of Asafo-Adjei *et al.* (2022b), the analysis employs 10 IMFs and a residue created using the I-CEEMDAN decomposition method for both sustainability and conventional ER. The properties of the mean period, Pearson product–moment correlation and variances are used to group the data into a variety of frequencies.

To support the reconstruction of the IMFs into many frequencies, the computations are displayed as supplemental files. With this method, the data's inherent complexity can be carefully examined in order to classify each IMF into its corresponding high, medium and low frequencies as well as the residual. The mean periods for the multi-frequencies for all variables are as follows: "(1) less than 30 days within less than 50 consecutive days from IMF1 to IMF4 (HFQ); (2) between 30–300 days within less than 3 consecutive years on 250 cumulative trading days from IMF1 and (3) more than 300 days whose sum from IMF1 is over 3 consecutive years but less than 7 years on an approximation of 250 trading days (LFQ)" (Asafo-Adjei *et al.*, 2022b, p. 12–13).

The residue, on the other hand, covers more than 7 years and 250 trade days. This is significant because it may be necessary to allocate adequate time periods to allow for a thorough evaluation of the nexus due to the delayed influence of price responses to information. Furthermore, the sample duration of this study allows for additional options besides solely depending on the information provided by existent literature, which may not always account for the simultaneous diverse dynamics of each IMF for each sampled set of data.

Table 2 presents two stationarity tests to examine whether or not the statistical properties of the ER vary with time. The augmented Dickey–Fuller (ADF) and KPSS tests are utilised in this study. The null hypothesis for the ADF test takes on a nonstationary series whereas the KPSS test suggests a stationary series. The tests are computed for all the multi-frequencies for each ER at the 1 and 5% significance levels.

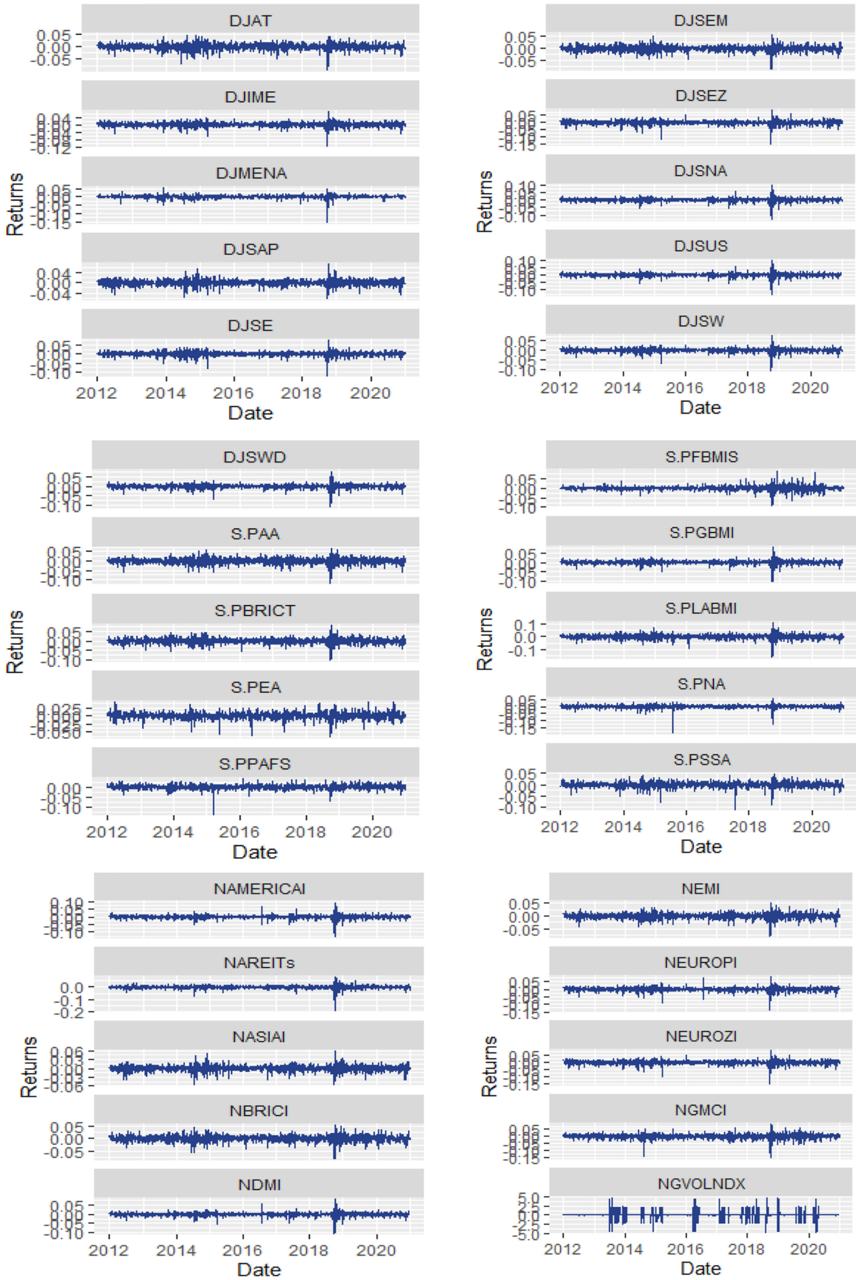


Figure 2.
Returns series

Source(s): Figure by authors

Table 2 provides reasonable evidence to conclude that almost all the equity returns are stationary at the high and medium frequencies. Strictly for the KPSS test, all the equity returns for the low frequency and residue are not stationary (*p-value* < 0.01). Although the

ER	Mean	SD	SKW	KTS	JB	KPSS	TRS
DJAT	−0.0002	0.01	−1.09	10.44	5269.36**	0.06	6.70*
DJIME	0.0003	0.01	−1.11	15.07	13196.42**	0.07	12.92**
DJMENA	0.0002	0.01	−4.00	70.26	401789.60**	0.14	50.32**
DJSAP	0.0001	0.01	−0.20	8.12	2311.88**	0.04	7.54*
DJSE	0.0002	0.01	−1.26	16.09	15572.37**	0.03	14.85**
DJSEM	0.0001	0.01	−0.73	9.75	4171.62**	0.08	25.11**
DJSEZ	0.0002	0.01	−1.46	19.70	25167.70**	0.04	9.45**
DJSNA	0.0005	0.01	−1.05	26.35	48123.20**	0.06	101.88**
DJSUS	0.0005	0.01	−0.99	25.01	42787.88**	0.05	96.95**
DJSW	0.0003	0.01	−1.42	21.19	29678.92**	0.07	45.83**
DJSWD	0.0003	0.01	−1.39	21.28	29948.29**	0.06	46.32**
S.PAA	−0.0001	0.01	−0.79	9.12	3493.25**	0.04	6.34*
S.PBRICT	0.0001	0.01	−0.74	9.83	4278.79**	0.19	37.44**
S.PEA	0.0001	0.01	−0.74	9.31	3674.49**	0.07	0.80
S.PFBMIS	0.0003	0.01	−0.47	15.57	13919.09**	0.16	13.12**
S.PGBMI	0.0004	0.01	−1.58	24.72	42181.89**	0.11	54.10**
S.PLABMI	−0.0003	0.02	−1.17	15.59	14349.77**	0.05	81.01**
S.PNA	0.0000	0.01	−4.98	83.15	571353.00**	0.05	20.63**
S.PPAFS	−0.0001	0.01	−1.46	21.28	30017.39**	0.03	4.33
S.PSSA	−0.0004	0.01	−1.27	13.14	9560.10**	0.20	1.95
NAMERICAI	0.0005	0.01	−1.13	24.44	40723.38**	0.06	93.24**
NAREITs	0.0003	0.01	−2.37	41.74	133424.90**	0.03	27.88**
NASIAI	0.0002	0.01	−0.40	7.81	2083.30**	0.03	5.19
NBRICI	0.0001	0.01	−0.72	8.77	3099.72**	0.05	25.03**
NDMI	0.0004	0.01	−1.40	24.13	39801.01**	0.05	61.23**
NEMI	0.0001	0.01	−0.80	10.28	4867.94**	0.06	25.09**
NEUROPI	0.0002	0.01	−1.46	21.41	30425.21**	0.04	0.06
NEUROZI	0.0002	0.01	−1.50	19.81	25543.58**	0.04	7.08*
NGMCI	0.0007	0.02	−1.17	13.51	10147.28**	0.06	43.28**
NGVOLNDX	0.0008	0.75	−0.05	19.54	23967.01**	0.01	83.88**

Note(s): The mean values are specifically kept in four decimal points due to zero redundancy. [*; **] show significance levels at 5 and 1% respectively. SD, SKW, KTS, JB, KPSS and TRS, respectively, denote standard deviation, skewness, kurtosis, Jarque-Bera, Kwiatkowski–Phillips–Schmidt–Shin and Teraesvirta's neural network tests
Source(s): Table by authors

Table 1. Descriptive statistics of equity returns

original series appears to be stationary which the test could not detect otherwise, it is the long-term trend and low frequency that vary with time. Accordingly, the dominant frequencies which are HFQ and MFQ drive the stationary series of the equities' original returns series. In this regard, the study concludes that stationarity is frequency-dependent.

Since financial time series are influenced by nonlinearity, the current study employs the TRS test which has linearity in the mean as the null hypothesis. In the TRS test, Taylor series expansion of the activation function is utilised to reach a fit test statistic (Teräsvirta, 1996; Zhang and Wang, 2011; Owusu Junior *et al.*, 2022). The TRS test is presented for HFQ, MFQ, LFQ and RESID for all the ER as shown in Table 3.

4.3 Information flows at multi-frequencies

We present an analysis of 20 sustainability and 10 conventional equity returns through the multi-frequency-based entropy approach at 95% confidence bounds. Specifically, the application of the multi-frequencies shows the relevance of multi-scales in financial time series in addressing the heterogeneous and adaptive dynamics of markets.

	ADF				KPSS			
Equities	HFQ	MFQ	LFQ	RESID	HFQ	MFQ	LFQ	RESID
DJAT	−17.70**	−8.15**	−6.60**	−17.83**	0.05	0.33	1.82**	20.48**
DJIME	−18.68**	−8.59**	−4.40**	−4.15**	0.07	0.02	0.94**	13.54**
DJMENA	−18.04**	−8.44**	−1.54	−23.16**	0.02	0.09	0.93**	5.92**
DJSAP	−16.78**	−8.47**	−0.84	−0.07**	0.02	0.25	2.28**	23.65**
DJSE	−16.90**	−9.92**	−1.21	−11.50**	0.03	0.03	1.33**	21.58**
DJSEM	−16.69**	−7.89**	−8.96**	1.02	0.04	0.05	1.85**	23.64**
DJSEZ	−18.90**	−7.84**	−6.46**	−6.83**	0.08	0.60*	2.33**	23.67**
DJSNA	−19.19**	−10.19**	−2.79	−1.49	0.06	0.04	1.17**	11.46**
DJSUS	−19.03**	−9.55**	−1.33	−26.35**	0.07	0.02	1.01**	12.98**
DJSW	−18.40**	−10.35**	−2.49	−6.25**	0.03	0.03	1.05**	13.29**
DJSWD	−18.22**	−8.78**	−0.58	−9.41**	0.02	0.02	0.94**	23.50**
S.PAA	−18.44**	−8.83**	−2.71	−28.39**	0.01	0.04	2.81**	15.45**
S.PBRICT	−16.94**	−7.65**	−5.94**	−2.85	0.13	0.17	4.84**	23.60**
S.PEA	−17.18**	−7.24**	−1.75	−9.76**	0.02	0.18	2.14**	23.65**
S.PFBMIS	−17.95**	−6.04**	−2.15	0.49	0.01	0.49*	4.32**	23.63**
S.PGBMI	−18.07**	−10.88**	−0.95	−12.88**	0.01	0.04	0.92**	19.22**
S.PLABMI	−17.59**	−7.96**	−1.00	−0.15	0.06	0.08	2.71**	23.63**
S.PNA	−16.40**	−7.46**	−1.68	−0.15	0.01	0.08**	0.84**	23.70**
S.PPAFS	−16.15**	−7.17**	−7.82**	−17.80**	0.08	0.21	1.75**	9.96**
S.PSSA	−17.87**	−8.99**	−2.46	−6.84**	0.04	0.03	2.34**	22.26**
NAMERICAI	−19.25**	−10.23**	−1.02	−25.66**	0.04	10.02	1.92**	6.84**
NAREITs	−16.58**	−8.95**	0.84	−3.18	0.03	0.04	3.10**	23.58**
NASIAI	−17.17**	−8.80**	−13.16**	0.38	0.02	0.06	5.35**	23.65**
NBRICI	−16.79**	−7.20**	−1.25	0.70	0.10	0.04	1.19**	23.65**
NDMI	−17.18**	−6.72**	−2.04	−0.09	0.02	0.04	3.69**	23.65**
NEMI	−17.44**	−7.77**	−0.98	−9.27**	0.07	0.08	2.95**	21.35**
NEUROPI	−17.16**	−8.31**	2.65	2.23	0.02	0.20	1.66**	22.97**
NEUROZI	−17.60**	−8.99**	−1.17	−22.51**	0.10	0.13	1.46**	4.95**
NGMCI	−18.01**	−9.07**	−7.27**	−1.85	0.01	0.10	2.43**	23.62**
NGVOLNDX	−12.46**	−10.28**	−2.61	10.17	0.09	0.59*	1.59**	22.45**

Note(s): [*, **] show significance levels at respectively 5 and 1%. HFQ, MFQ, LFQ and RESID denote high frequency, medium frequency, low frequency and residue, respectively
Source(s): Table by authors

Table 2.
Stationarity tests of equity returns

To provide a smooth interpretation of the outcomes, the presence of a negative ETE signifies that knowledge of an equity index indicates a higher risk coverage for the others whilst a positive ETE implies that awareness of an equity index plunges the risk of the others (Adam, 2020; Asafo-Adjei *et al.*, 2022a). The study assigns high weight to the tails for low values of q. Hence, following extant literature, q from the Rényi effective transfer entropy (RETE) is set to 0.3 to offer more weights to the tails, which bears direct implications for revealing richer information at low probability events of extreme markets outcomes.

Since information flows between stock markets occur between the entire market and its constituents as well as other financial markets (Kwon and Yang, 2008; Osei and Adam, 2020), the study examines information flows between regional equities as constituents and global equities and advanced markets as the entire market. This is not overwhelming because stock markets operate in a nonisolated system, which interacts and exchanges information with the real economy (Osei and Adam, 2020). For this reason, information flows are presented between other ER and global indices such as S.PGBMI, DJSW, DJSWD and NGMCI. Findings are presented for S.PGBMI and NGMCI as proxies for global indices in sustainability and conventional equities, respectively, and the remaining global indices are attached as supplementary for comparison (see, Tables S2–S5).

Equities	HFQ	Teraesvirta's neural network test (TRS) MFQ	LFQ	RESID
DJAT	25.12**	0.09	12.46**	694.98**
DJIME	35.65**	0.53	1.11	7.02*
DJMENA	71.42**	2.08	4.76	15.88**
DJSAP	23.95**	0.12	7.48*	6256.40**
DJSE	39.18**	0.04	2.44	3707.20**
DJSEM	38.22**	0.09	0.01	33.95**
DJSEZ	20.24**	0.28	1.09	5715.50**
DJSNA	133.61**	0.36	5.95	538.45**
DJSUS	123.85**	0.13	1.98	403.76**
DJSW	79.07**	0.39	0.13	177.20**
DJSWD	80.84**	0.39	6.74*	3228.10**
S.PAA	19.14**	0.74	0.08	486.18**
S.PBRICT	59.79**	0.18	50.88**	4939.50**
S.PEA	4.11	0.11	26.14**	6569.90**
S.PFBMIS	19.61**	2.55	9.61**	6514.40**
S.PGBMI	118.74**	1.21	7.82*	1051.80**
S.PLABMI	160.58**	0.36	6.88*	4919.00**
S.PNA	46.19**	0.9	2.06	3620.40**
S.PPAFS	1.18	0.31	0.54	90.71**
S.PSSA	6.28*	0.01	2.11	3001.60**
NAMERICAI	129.79**	0.45	6.62*	0.02
NAREITs	41.64**	0.10	4.71	4.56
NASIAI	25.02**	0.15	5.11	944.81**
NBRICI	38.47**	0.11	1.30	1789.50**
NDMI	179.47**	5.52	2.41	5022.30**
NEMI	55.47**	0.12	12.56**	2120.70**
NEUROPI	2.78	0.62	53.21**	3702.60**
NEUROZI	17.15**	0.20	6.17*	286.98**
NGMCI	58.41**	0.32	2.82	10216.00**
NGVOLNDX	95.15**	1.15	0.07	2230.80**

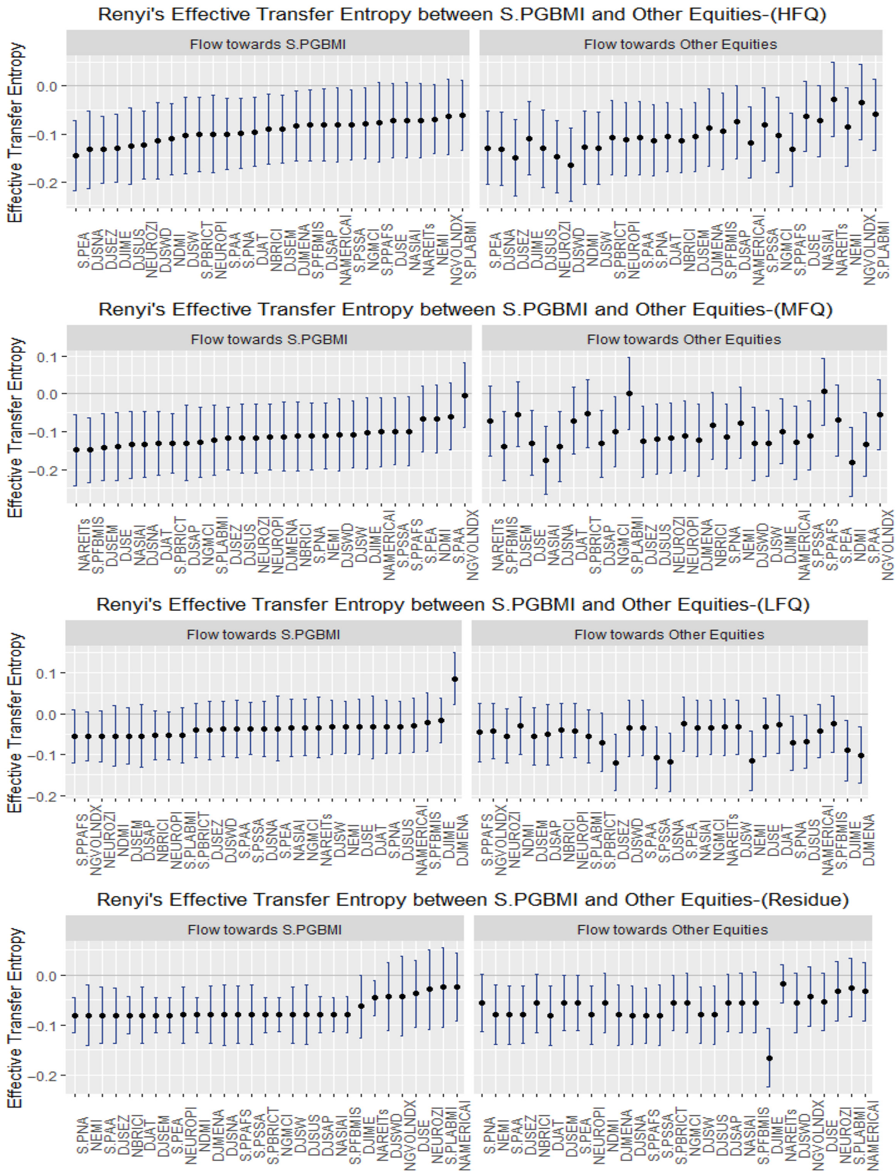
Note(s): [*; **] show significance levels at respectively 5 and 1%
Source(s): Table by authors

Table 3. Linearity test of equity returns

Figure 3 displays information flows between S.PGBMI and the remaining 29 equities at multi-frequencies. It shows information flows towards S.PGBMI and flows from S.PGBMI. The findings provided here depict similar outcomes for DJSW, DJSWD and NGMCI as shown in supplementary. Numerical outputs of the information flows are shown in Table 4.

It can be seen that significant negative information is generally transmitted towards S.PGBMI and from S.PGBMI in the short, medium and long terms in addition to the residue as shown in Figure 3. The negative information flows even become more significant in the HFQ, MFQ and residue, highlighting their dominance in the information flow dynamics with S.PGBMI. A scan through the RETE plots indicates that NASDAQ 100 Volatility Target index (NVOLNDX) demonstrates the weakest flow of information with S.PGBMI. This implies that NVOLNDX as a measure of volatility index depicts less connectedness with S.PGBMI and with all other equities as presented in the supplementary files. This highlights the resistance of S.PGBMI as a proxy for global sustainability index against shocks from NVOLNDX. Accordingly, it becomes difficult for the S.PGBMI to be susceptible to contagion from NVOLNDX and vice versa.

As revealed by Asafo-Adjei *et al.* (2022b) on the significant positive correlation among the SEs at most frequencies driving their persisting convergence as found in the unconditional correlation matrix and wavelet multiple in the study of Asafo-Adjei *et al.* (2022c), information transmission among them is mostly rather negative and significant. This concurs the



Source(s): Figure by authors

Figure 3.
Multi-frequency information flows between S.PGBMI and other ER

findings by Asafo-Adjei *et al.* (2022a), Boateng *et al.* (2022), Bossman (2021) and Bossman *et al.* (2022a). This accentuates that knowledge of S.PGBMI indicates a higher risk coverage for the other ER and vice versa. This is pertinent for portfolio diversification in the sense that information transmitted from S.PGBMI plummets the performance of other ER in the short and medium term, as well as the long-term trend.

Equities	Flows towards global equities HFQ	MFQ	LFQ	RESID	Flows towards other equities HFQ	MFQ	LFQ	RESID
	S.PGBMI				Others			
DJAT	−0.096	−0.132	−0.033	−0.081	−0.106	−0.071	−0.027	−0.081
DJIME	−0.129	−0.103	−0.017	−0.063	−0.109	−0.099	−0.090	−0.166
DJMENA	−0.082	−0.113	0.086	−0.080	−0.087	−0.123	−0.101	−0.080
DJSAP	−0.081	−0.130	−0.054	−0.080	−0.075	−0.132	−0.051	−0.056
DJSE	−0.072	−0.139	−0.033	−0.038	−0.063	−0.130	−0.033	−0.053
DJSEM	−0.090	−0.141	−0.055	−0.081	−0.106	−0.054	−0.055	−0.056
DJSEZ	−0.133	−0.118	−0.041	−0.081	−0.149	−0.126	−0.119	−0.080
DJSNA	−0.133	−0.133	−0.037	−0.080	−0.131	−0.140	−0.119	−0.081
DJSUS	−0.125	−0.118	−0.033	−0.080	−0.130	−0.120	−0.069	−0.080
DJSW	−0.104	−0.108	−0.033	−0.080	−0.130	−0.131	−0.033	−0.080
DJSWD	−0.113	−0.108	−0.038	−0.043	−0.164	−0.132	−0.036	−0.056
S.PAA	−0.100	−0.059	−0.037	−0.081	−0.108	−0.133	−0.034	−0.080
S.PBRICT	−0.101	−0.131	−0.041	−0.080	−0.108	−0.052	−0.071	−0.056
S.PEA	−0.145	−0.066	−0.036	−0.081	−0.130	−0.070	−0.025	−0.056
S.PFBMIS	−0.082	−0.149	−0.021	−0.080	−0.094	−0.139	−0.025	−0.055
S.PLABMI	−0.061	−0.122	−0.054	−0.025	−0.060	0.001	−0.055	−0.026
S.PNA	−0.098	−0.112	−0.033	−0.081	−0.114	−0.113	−0.073	−0.056
S.PPAFS	−0.076	−0.099	−0.055	−0.080	−0.132	0.005	−0.046	−0.081
S.PSSA	−0.080	−0.099	−0.037	−0.080	−0.080	−0.110	−0.107	−0.081
NAMERICAI	−0.081	−0.101	−0.029	−0.025	−0.118	−0.129	−0.042	−0.033
NAREITs	−0.071	−0.149	−0.034	−0.046	−0.028	−0.072	−0.033	−0.017
NASIAI	−0.072	−0.135	−0.035	−0.080	−0.073	−0.175	−0.036	−0.056
NBRICI	−0.090	−0.112	−0.054	−0.081	−0.115	−0.084	−0.040	−0.056
NDMI	−0.110	−0.066	−0.055	−0.080	−0.128	−0.180	−0.031	−0.056
NEMI	−0.069	−0.111	−0.033	−0.081	−0.085	−0.077	−0.115	−0.080
NEUROPI	−0.100	−0.114	−0.054	−0.081	−0.111	−0.111	−0.042	−0.080
NEUROZI	−0.122	−0.118	−0.055	−0.029	−0.147	−0.116	−0.055	−0.033
NGMCI	−0.078	−0.129	−0.034	−0.080	−0.102	−0.101	−0.035	−0.056
NGVOLNDX	−0.064	−0.003	−0.055	−0.043	−0.034	−0.054	−0.043	−0.043
	NGMCI				Others			
DJAT	−0.103	−0.075	−0.025	−0.056	−0.119	−0.011	−0.047	−0.081
DJIME	−0.052	−0.096	−0.036	−0.056	−0.104	−0.104	−0.063	−0.079
DJMENA	−0.029	−0.014	−0.036	−0.056	−0.120	−0.147	−0.020	−0.080
DJSAP	−0.067	−0.181	−0.033	−0.094	−0.088	−0.185	−0.078	−0.094
DJSE	−0.099	−0.173	−0.054	−0.024	−0.086	−0.100	−0.054	−0.053
DJSEM	−0.040	−0.161	−0.033	−0.094	−0.112	−0.050	−0.034	−0.094
DJSEZ	−0.068	−0.031	−0.027	−0.047	−0.073	−0.114	−0.053	−0.065
DJSNA	−0.138	−0.140	−0.055	−0.056	−0.126	−0.034	−0.038	−0.080
DJSUS	−0.122	−0.085	−0.034	−0.056	−0.124	−0.075	−0.117	−0.081
DJSW	−0.101	−0.107	−0.044	−0.056	−0.091	−0.064	−0.048	−0.080
DJSWD	−0.092	−0.109	−0.033	−0.018	−0.057	−0.059	−0.038	−0.033
S.PAA	−0.084	−0.148	−0.055	−0.056	−0.093	−0.173	−0.055	−0.081
S.PBRICT	−0.093	−0.117	−0.044	−0.094	−0.086	−0.031	−0.070	−0.093
S.PEA	−0.126	−0.071	−0.024	−0.093	−0.091	−0.098	−0.023	−0.093
S.PFBMIS	−0.101	−0.131	−0.043	−0.093	−0.085	−0.089	−0.040	−0.093
S.PGBMI	−0.098	−0.108	−0.035	−0.056	−0.080	−0.123	−0.034	−0.081
S.PLABMI	−0.060	−0.119	−0.054	−0.040	−0.103	−0.114	−0.054	−0.059
S.PNA	−0.063	−0.073	−0.055	−0.094	−0.066	−0.151	−0.045	−0.093
S.PPAFS	−0.062	−0.075	−0.055	−0.056	−0.106	−0.050	−0.041	−0.081
S.PSSA	−0.071	−0.105	−0.038	−0.056	−0.088	−0.095	−0.104	−0.081

(*continued*)

Table 4.
Multi-frequency entropy analysis of information flows between global equities and constituents

	NGMCI					Others		
NAMERICAI	−0.108	−0.112	−0.056	−0.017	−0.122	−0.031	−0.048	−0.034
NAREITs	−0.081	−0.115	−0.054	−0.032	−0.052	−0.077	−0.054	−0.017
NASIAI	−0.111	−0.137	−0.054	−0.093	−0.089	−0.126	−0.054	−0.094
NBRICI	−0.042	−0.127	−0.034	−0.093	−0.060	−0.007	−0.066	−0.093
NDMI	−0.093	−0.102	−0.042	−0.094	−0.084	−0.087	−0.021	−0.093
NEMI	−0.039	−0.024	−0.033	−0.056	−0.091	−0.111	−0.117	−0.080
NEUROPI	−0.060	−0.106	−0.055	−0.056	−0.089	−0.058	−0.042	−0.081
NEUROZI	−0.080	−0.091	−0.056	−0.056	−0.070	−0.090	−0.055	−0.081
NGVOLNDX	−0.012	−0.036	−0.025	−0.056	−0.077	0.089	−0.066	−0.081

Source(s): Table by authors

Table 4.

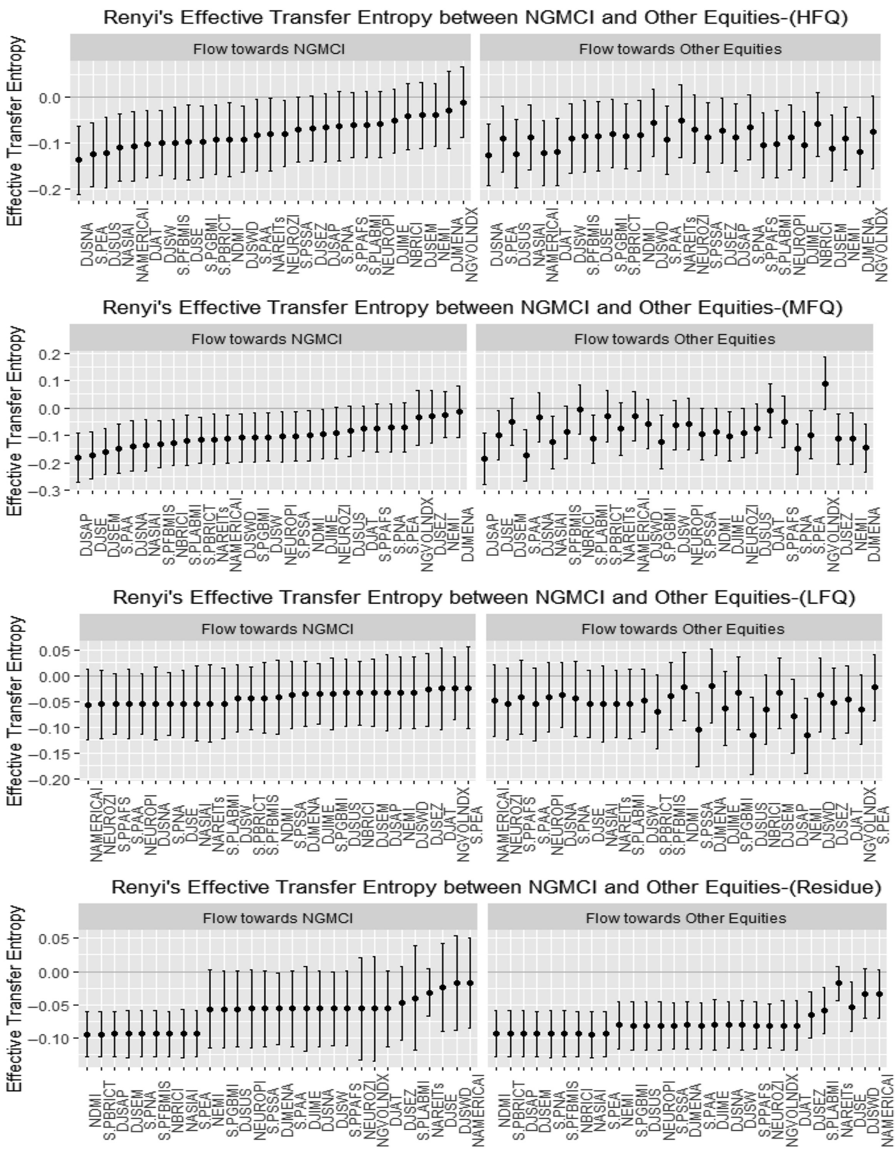
Nonetheless, the patterns of information flows among the SEs vary from one frequency to another as revealed numerous studies on information flows (Boateng *et al.*, 2022, Bossman, 2021; Bossman *et al.*, 2022a; Owusu Junior *et al.*, 2021b, etc.). Particularly, SEs transmit significant negative information towards S.PGBMI at the HFQ except for S.PLABMI, DJSE, S.PPAFS and S.PSSA, but except for S.PEA and S.PAA at the MFQ. At the LFQ, except for DJMENA, all the sustainability equity indices transmit no information to S.PGBMI. Moreover, the residue indicates that all sustainability equity indices but S.PLABMI, DJSE, DJSWD and DJIME transmit significant negative information to S.PGBMI. This demonstrates the degree to which sustainability equity securities using S.PGBMI as a worldwide index exhibit varied and adaptive behaviour. Given the large negative information flows between the returns of S.PGBMI and all other sustainability stocks, investors interested in SRI would choose to choose from a variety of SEs to build a trustworthy portfolio.

It can further be noticed that information flows for most SEs are bi-directional for HFQ, MFQ and residue. This shows that sustainability equity indices exhibit similar dynamics of information transfer to a global index. As such most of the sustainability equity indices can equally observe the behaviour of S.PGBMI from the standpoint of irrational investors at varying levels of multi-frequencies revealing markets inefficiencies.

However, the insignificant negative information flows at LFQ for most sustainability equity indices manifest that in the long term, the markets begin to submerge from their longstanding interactions to induce convoluting predictions which contradicts the outcome by Asafo-Adjei *et al.* (2022a) during the COVID-19 pandemic. Accordingly, the efficient adjustment of prices to information is a key feature of market circumstances. As a result, there is agreement among market participants at the LFQ regarding the significance of recent information for each security's present price and distribution of its future price (Fama, 1970). For logical investors who want to maximise their utility in accordance with Neoclassical theory, they would take advantage of the market by (1) identifying patterns in price fluctuations or information flows in the HFQ and MFQ and (2) purchasing the security to build dependable portfolios.

Nonetheless, as buying drives up the price of an asset and selling drives it down, the information the arbitrageur trader had about the market is mirrored in the asset prices, suggesting that there may be patterns that can be exploited but that are not permanent. This is due to the fact that reacting to information changes the pricing, which eliminates patterns as shown in the LFQ.

In comparison with conventional equities, Figure 4 presents information flows with NGMCI in across investment horizons. This would inform investors on the effective allocation of assets, rebalancing or redeployment of their portfolios in the short, medium and long terms with SRI and the conventional way of investing in perspective.



Source(s): Figure by authors

Figure 4.
Multi-frequency information flows between NGMCI and other equities

From Figure 4, we find similar significant flows of information among the equities as noticed in Figure 3. However, in the residue (very long term) information flows with the NGMCI as a global proxy for CE transmits and receives more negative information with both sustainability and conventional equity returns. On the other hand, in the short and medium frequencies, information flows with the S.PGBMI are more negative and significant relative to the NGMCI. Conversely, all the global indices demonstrate no significant information flows.

Having in mind, the wider representation of global indices, we advocate that information flows with SEs enhance diversification potentials in the short and medium terms, whereas information flows with CEs exacerbate diversification benefits in the long-term deterministic trend representing over 7 years of the sampled period on a 250 trading days. Hence, speculative investors of SEs can form a diversified portfolio in the very long term when they include relevant indices of CEs. On the other hand, short- and medium-term investors are better off with a diversified portfolio when they concentrate on SRI. Accordingly, existing investors of CEs can still maintain their portfolio choices but should have plans for considering SRI since its benefit exceeds the cost.

4.4. Discussion

The study revealed significant negative information flows toward S.PGBMI and from S.PGBMI in the short, medium and long terms in addition to the residue as found by existing studies on other financial assets but with some degree of differences in outcomes (Adam, 2020; Boateng *et al.*, 2022; Bossman, 2021; Bossman *et al.*, 2022a; Owusu Junior *et al.*, 2021b). The negative information flows even became more significant in the HFQ, MFQ and residue, highlighting their dominance in the information flow dynamics with S.PGBMI and NGMCI. This explains that knowledge of S.PGBMI and NGMCI designates a higher risk coverage for the other ER and vice versa, thereby magnifying diversification benefits. The study further found that information flows for most SEs are bi-directional for HFQ, MFQ and residue confirming the similar dynamics of information flows to a global index despite their asymmetric behaviour regarding volatilities (Irfan *et al.*, 2021). The SEs, however, depict asymmetric relationships from one frequency to another. As such most of the sustainability equity indices can equally observe the behaviour of S.PGBMI at varying levels of multi-frequencies. Accordingly, investors can form reliable portfolio by concentrating information flow between the global and constituents' assets at the high and medium frequencies and residue representing short-, medium-, and very long-term dynamics.

Nonetheless, the insignificant negative information flows at LFQ for most sustainability equity indices manifest that in the long term, the markets begin to submerge their longstanding interactions to hinder predictions or exploitations of patterns. At the low frequency, this may prohibit analysts who aspire to be with a firm based on the firm's inclusion on the sustainability index as found by Durand *et al.* (2019). However, exploitation of the market becomes advantageous to short- and medium-term investors as well as the very long-term representing over 7 years on about 250 trading days for long-term investors and institutional investors alike. Generally, the examination of CSR activities is an impetus or important requirement for asset allocation as averred by Consolandi *et al.* (2009) and Helliar *et al.* (2022).

5. Conclusions

This study investigated information flows among constituents and global – sustainability and conventional equity returns across investment horizons. For this reason, a multi-frequency-dependent technique was employed to address the heterogeneous (Müller *et al.*, 1997) and adaptive (Lo, 2004) behaviours. Accordingly, the I-CEEMDAN-based cluster analysis RETE were utilised in this study. The study's analyses were mostly focused on sustainability-related stocks in comparison to conventional stocks. The daily data, which included 2,102 observations, run from November 12th, 2012 to December 2nd, 2021.

We found significant information flows among the constituents and their global indices. Information flow for most sustainability and conventional equity returns were found to be negative and bidirectional at multi-frequencies, except for the low frequency.

The study concludes that negative information transmission between constituents of SEs and their global index is multi-frequency dependent. The knowledge of a global index indicates a higher risk coverage for sustainability equity returns as constituents and vice versa to warrant diversification benefits. Moreover, the information the arbitrageur trader had concerning the market in the short and medium terms is reflected in the asset prices, suggesting that indeed there could be patterns that can be exploited, but not everlasting. This explains that the behaviour of the markets is heterogeneous and adaptive due to the behavioural intentions of market participants, especially in the short and medium terms, but this effect dissipates in the low frequency suggesting markets efficiency. Overall, the markets are inefficient at various frequencies of varying dynamics but become efficient only at the low frequency (long term) in terms of unpredictable patterns of information flows.

It is suggested that rational investors who want to maximise their utility in accordance with Neoclassical theory should take advantage of the market in the following ways: (1) identify patterns in short- and medium-term price changes or information flows and (2) buy the security to build reliable portfolios. This is pertinent because the exploited patterns are not persisting. Consequently, responding to the information affects the prices which induce the patterns to be expunged as witnessed in the low frequency. For reliable portfolio returns, it is important for investors to form portfolio between the global and constituents' assets at the high and medium frequency and residue representing short-, medium- and very long-term dynamics.

Future research can focus on information flow among sustainability stocks before and during the COVID-19 era to examine how it affected the pre-existing connections. Moreover, studies may delve into regional blocs to examine the pattern of country or firm-specific similarities, interdependencies and information flows among sustainability equity indices.

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Supplementary materials

SN	Sustainability equity indices	Code
1	Dow Jones Africa Titans 50 Index	DJAT
2	Dow Jones Islamic Market Europe Index	DJIME
3	Dow Jones MENA Index	DJMENA
4	Dow Jones Sustainability Asia Pacific Index	DJSAP
5	Dow Jones Sustainability Europe Index	DJSE
6	Dow Jones Sustainability Emerging Markets Index	DJSEM
7	Dow Jones Sustainability Eurozone Region Index	DJSEZ
8	Dow Jones Sustainability North America Index	DJSNA
9	Dow Jones Sustainability U.S. Index	DJSUS
10	Dow Jones Sustainability World Index	DJSW
11	Dow Jones Sustainability World Developed Index	DJSWD
12	S&P All Africa	S.PAA
13	S&P BRICT Index	S.PBRICT
14	S&P East Africa	S.PEA
15	S&P Frontier BMI Shariah	S.PFBMIS
16	S&P Global BMI	S.PGBMI
17	S&P Latin America BMI	S.PLABMI
18	S&P North Africa	S.PNA
19	S&P Africa Frontier Shariah Index	S.PPAFS
20	S&P All Sub-Saharan Africa ex-South Africa Index	S.PSSA
Control variables (conventional equities)		
1	NASDAQ America Index	NAMERICAI
2	NAREIT Global Real Estate Index	NAREITs
3	NASDAQ ASIA Index	NASIAI
4	NASDAQ BRIC Index	NBRICI
5	NASDAQ Developed Markets Index	NDMI
6	NASDAQ Emerging Markets Index	NEMI
7	NASDAQ Europe Index	NEUROPI
8	NASDAQ Eurozone Index	NEUROZI
9	NASDAQ Global Market Composite Index	NGMCI
10	NASDAQ 100 Volatility Target	NGVOLNDX

Source(s): Table by authors

Table S1.
Equity indices

	Flows towards global equities				Flows towards other equities			
	HFQ	MFQ	LFQ	RESID	HFQ	MFQ	LFQ	RESID
Equities	DJSW				Others			
DJAT	−0.110	−0.137	−0.051	−0.081	−0.064	−0.138	−0.033	−0.080
DJIME	−0.122	−0.132	−0.019	−0.062	−0.132	−0.132	−0.137	−0.111
DJMENA	−0.068	−0.101	−0.033	−0.080	−0.100	−0.101	−0.017	−0.080
DJSAP	−0.124	−0.147	−0.054	−0.081	−0.077	−0.090	−0.050	−0.055
DJSE	−0.081	−0.157	−0.054	−0.036	−0.043	−0.116	−0.055	−0.054
DJSEM	−0.111	−0.177	−0.015	−0.081	−0.108	−0.134	−0.017	−0.056
DJSEZ	−0.137	−0.072	−0.033	−0.081	−0.108	−0.101	−0.060	−0.081
DJSNA	−0.151	−0.141	−0.055	−0.082	−0.134	−0.135	−0.044	−0.081
DJSUS	−0.153	−0.137	−0.033	−0.059	−0.142	−0.078	−0.071	−0.058
DJSWD	−0.109	−0.182	−0.038	−0.042	−0.103	−0.178	−0.042	−0.054
S.PAA	−0.135	−0.118	−0.054	−0.067	−0.141	−0.146	−0.054	−0.072
S.PBRICT	−0.108	−0.123	−0.038	−0.081	−0.081	−0.039	−0.076	−0.055
S.PEA	−0.132	−0.061	−0.039	−0.081	−0.101	−0.070	−0.033	−0.056
S.PFBMIS	−0.084	−0.106	−0.037	−0.081	−0.085	−0.134	−0.036	−0.055
S.PGBMI	−0.130	−0.136	−0.034	−0.081	−0.107	−0.116	−0.033	−0.081
S.PLABMI	−0.118	−0.126	−0.056	−0.025	−0.107	−0.109	−0.055	−0.026
S.PNA	−0.008	−0.080	−0.054	−0.081	−0.097	−0.110	−0.095	−0.056
S.PPAFS	−0.069	−0.032	−0.055	−0.056	−0.081	−0.070	−0.049	−0.064
S.PSSA	−0.133	−0.130	−0.018	−0.081	−0.065	−0.122	−0.122	−0.081
NAMERICAI	−0.151	−0.138	−0.043	−0.010	−0.136	−0.114	−0.040	−0.013
NAREITs	−0.079	−0.136	−0.055	−0.046	−0.060	−0.095	−0.055	−0.017
NASIAI	−0.109	−0.149	−0.054	−0.081	−0.045	−0.128	−0.055	−0.055
NBRICI	−0.083	−0.123	−0.016	−0.080	−0.102	−0.075	−0.046	−0.056
NDMI	−0.148	−0.117	−0.055	−0.081	−0.145	−0.070	−0.036	−0.056
NEMI	−0.089	−0.163	−0.055	−0.081	−0.075	−0.126	−0.037	−0.080
NEUROPI	−0.118	−0.124	−0.055	−0.080	−0.097	−0.118	−0.042	−0.080
NEUROZI	−0.130	−0.124	−0.034	−0.042	−0.115	−0.123	−0.033	−0.042
NGMCI	−0.099	−0.065	−0.049	−0.081	−0.095	−0.109	−0.044	−0.056
NGVOLNDX	0.008	0.046	−0.022	−0.042	−0.021	−0.009	−0.046	−0.043
	DJSWD				Others			
DJAT	−0.072	−0.170	−0.038	−0.055	−0.042	−0.157	−0.024	−0.042
DJIME	−0.121	−0.129	−0.019	−0.054	−0.128	−0.140	−0.090	−0.033
DJMENA	−0.070	−0.102	−0.035	−0.055	−0.104	−0.106	−0.025	−0.042
DJSAP	−0.127	−0.130	−0.054	−0.033	−0.092	−0.139	−0.049	−0.018
DJSE	−0.058	−0.144	−0.055	−0.055	−0.048	−0.111	−0.055	−0.054
DJSEM	−0.078	−0.171	−0.037	−0.033	−0.067	−0.143	−0.039	−0.017
DJSEZ	−0.093	−0.065	−0.055	−0.037	−0.086	−0.095	−0.030	−0.029
DJSNA	−0.148	−0.144	−0.033	−0.055	−0.127	−0.129	−0.070	−0.042
DJSUS	−0.157	−0.133	−0.055	−0.054	−0.135	−0.118	−0.046	−0.042
DJSW	−0.106	−0.177	−0.042	−0.054	−0.107	−0.180	−0.038	−0.043
S.PAA	−0.105	−0.117	−0.055	−0.055	−0.115	−0.114	−0.055	−0.042
S.PBRICT	−0.100	−0.121	−0.055	−0.033	−0.052	−0.043	−0.043	−0.018
S.PEA	−0.128	−0.067	−0.055	−0.033	−0.100	−0.116	−0.042	−0.017
S.PFBMIS	−0.093	−0.115	−0.033	−0.033	−0.094	−0.133	−0.033	−0.017
S.PGBMI	−0.158	−0.135	−0.036	−0.055	−0.117	−0.111	−0.037	−0.042
S.PLABMI	−0.100	−0.134	−0.034	−0.033	−0.084	−0.117	−0.032	−0.026

Table S2.
Multi-frequency entropy analysis of information flows between other global equities and constituents

(*continued*)

	DJSWD				Others			
S.PNA	−0.045	−0.074	−0.055	−0.033	−0.121	−0.114	−0.044	−0.017
S.PPAFS	−0.062	−0.070	−0.054	−0.055	−0.086	−0.066	−0.048	−0.042
S.PSSA	−0.092	−0.133	−0.055	−0.055	−0.069	−0.117	−0.089	−0.042
NAMERICAI	−0.153	−0.143	−0.034	−0.055	−0.127	−0.114	−0.033	−0.055
NAREITs	−0.089	−0.131	−0.055	−0.042	−0.064	−0.101	−0.055	−0.012
NASIAI	−0.099	−0.142	−0.054	−0.032	−0.075	−0.130	−0.054	−0.017
NBRICI	−0.071	−0.079	−0.036	−0.033	−0.098	−0.024	−0.022	−0.017
NDMI	−0.153	−0.132	−0.055	−0.033	−0.152	−0.085	−0.031	−0.017
NEMI	−0.056	−0.152	−0.055	−0.055	−0.055	−0.130	−0.036	−0.042
NEUROPI	−0.069	−0.119	−0.055	−0.032	−0.062	−0.126	−0.042	−0.026
NEUROZI	−0.093	−0.111	−0.034	−0.033	−0.073	−0.118	−0.035	−0.026
NGMCI	−0.052	−0.060	−0.037	−0.033	−0.089	−0.104	−0.033	−0.017
NGVOLNDX	−0.005	0.051	−0.036	−0.033	−0.015	−0.002	−0.117	−0.026

Source(s): Table by authors

Table S2.

Table S3.
Sustainability equity (Dow Jones) measures of IMFs obtained through I-CEEMDAN

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	RESID
						DJAT					
μ	2.79	5.70	11.24	22.85	44.72	75.07	161.69	300.29	420.40	700.67	
ρ	0.71**	0.5**	0.41**	0.25**	0.22**	0.11**	0.12**	0.05**	0.05*	0.01	−0.01
σ_1^2	50.93%	17.13%	12.06%	6.67%	4.69%	1.29%	1.19%	0.70%	0.33	0.03%	0.01%
σ_2^2	50.93%	17.13%	12.06%	6.67%	4.69%	1.29%	1.19%	0.70%	0.33	0.03%	0.01%
						DJIME					
μ	2.75	5.65	10.89	20.61	36.88	70.07	140.13	210.20	350.33	525.50	
ρ	0.74**	0.45**	0.32**	0.20**	0.17**	0.12**	0.10**	0.04*	0.04*	0.01	−0.02
σ_1^2	59.78%	20.90%	12.08%	6.77%	2.80%	1.42%	1.11%	0.27%	0.40%	0.06%	0.01%
σ_2^2	59.78%	20.90%	12.08%	6.77%	2.80%	1.42%	1.11%	0.27%	0.40%	0.06%	0.01%
						DJMENA					
μ	2.68	5.35	10.72	20.02	38.22	67.81	105.10	175.17	262.75	420.40	
ρ	0.68**	0.50**	0.32**	0.24**	0.19**	0.15**	0.10**	0.08**	0.04*	0.08**	0.03
σ_1^2	50.58%	24.60%	10.10%	5.98%	5.29%	3.58%	1.32%	1.64%	0.68%	1.0%	0.13%
σ_2^2	50.58%	24.60%	10.10%	5.98%	5.29%	3.58%	1.32%	1.64%	0.68%	1.0%	0.13%
						DJSAP					
μ	2.74	5.53	10.62	21.45	40.42	84.08	140.13	233.56	420.4	525.50	
ρ	0.72**	0.49**	0.34**	0.24**	0.15**	0.12**	0.10**	0.05*	0.03	0.01	0.01
σ_1^2	54.97%	23.40%	10.74%	7.91%	2.65%	1.69%	0.72%	0.51%	0.02%	0.02%	0.01%
σ_2^2	54.97%	23.40%	10.74%	7.91%	2.65%	1.69%	0.72%	0.51%	0.02%	0.02%	0.01%
						DJSE					
μ	2.72	5.52	10.95	21.23	40.42	70.07	116.78	191.09	300.29	420.40	
ρ	0.76**	0.44**	0.33**	0.21**	0.18**	0.12**	0.09**	0.06**	0.05*	0.02	−0.01
σ_1^2	60.38%	17.44%	11.26%	7.25%	3.20%	1.43%	0.70%	0.26%	0.18%	0.04%	0.02%
σ_2^2	60.38%	17.44%	11.26%	7.25%	3.20%	1.43%	0.70%	0.26%	0.18%	0.04%	0.02%
						DJSEM					
μ	2.80	5.87	11.68	23.36	50.05	95.55	175.17	300.29	420.40	700.67	
ρ	0.73**	0.49**	0.36**	0.26**	0.17**	0.14**	0.09**	0.06**	0.03	0.01	0.02
σ_1^2	52.72%	19.31%	10.42%	6.56%	3.84%	2.71%	0.85%	0.51%	0.28%	0.17%	0.01%
σ_2^2	52.72%	19.31%	10.42%	6.56%	3.84%	2.71%	0.85%	0.51%	0.28%	0.17%	0.01%

(*continued*)

Table S3.

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	RESID
						DJSEZ					
μ	2.71	5.59	10.62	20.81	38.22	77.85	161.69	300.29	420.40	700.67	
ρ	0.73**	0.46**	0.37**	0.23**	0.19**	0.13**	0.07**	0.05*	0.01	0.01	−0.01
σ_1^2	55.97%	18.07%	13.18%	5.47%	3.86%	2.49%	1.55%	0.23%	0.12%	0.09%	0.02%
σ_2^2	55.97%	18.07%	13.18%	5.47%	3.86%	2.49%	1.55%	0.23%	0.12%	0.09%	0.02%
						DJSNA					
μ	2.73	5.36	10.20	18.94	35.63	61.82	110.63	161.69	300.29	420.40	
ρ	0.82**	0.40**	0.31**	0.21**	0.17**	0.13**	0.08**	0.05*	0.04*	0.01	0.02
σ_1^2	66.12%	12.71%	8.63%	3.93%	3.20%	1.47%	1.13%	0.42%	0.21%	0.03%	0.01%
σ_2^2	66.12%	12.71%	8.63%	3.93%	3.20%	1.47%	1.13%	0.42%	0.21%	0.03%	0.01%
						DJSUS					
μ	2.74	5.29	10.11	18.44	33.37	60.06	105.10	175.17	300.29	420.40	
ρ	0.82**	0.40**	0.30**	0.20**	0.17**	0.13**	0.09**	0.04*	0.03	0.02	0.02
σ_1^2	66.85%	13.02%	8.35%	3.51%	3.32%	1.60%	1.10%	0.27%	0.18%	0.06%	0.16%
σ_2^2	66.85%	13.02%	8.35%	3.51%	3.32%	1.60%	1.10%	0.27%	0.18%	0.06%	0.16%
						DJSW					
μ	2.79	5.68	10.89	20.81	36.24	63.70	116.78	150.14	350.33	525.50	
ρ	0.76**	0.47**	0.36**	0.20**	0.20**	0.14**	0.09**	0.06**	0.05*	0.03	0.02
σ_1^2	55.33%	15.63%	11.41%	7.13%	4.08%	1.73%	1.07%	0.50%	0.38%	0.02%	0.01%
σ_2^2	55.33%	15.63%	11.41%	7.13%	4.08%	1.73%	1.07%	0.50%	0.38%	0.02%	0.01%
						DJSWD					
μ	2.78	5.70	10.89	20.02	37.54	65.69	123.65	210.20	300.36	420.40	
ρ	0.76**	0.47**	0.35**	0.20**	0.20**	0.13**	0.09**	0.04*	0.04*	0.04*	0.01
σ_1^2	55.95%	15.58%	10.82%	7.03%	4.60%	1.71%	1.2%	0.26%	0.24%	0.10%	0.05%
σ_2^2	55.95%	15.58%	10.82%	7.03%	4.60%	1.71%	1.2%	0.26%	0.24%	0.10%	0.05%

Note(s): μ, ρ, σ_1^2 and σ_2^2 denote mean period, Pearson product moment correlations, variance as % of observed and variance as % of the sum of all IMFs and residue. [*; **] show significance levels at 5 and 1% respectively

Source(s): Table by authors

Table S4. Sustainability equities (S&P) measures of IMFs obtained through I-CEEMDAN

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMFF9	IMF10	RESID
						S.PAA					
μ	2.75	5.40	10.41	20.41	39.66	65.69	116.78	191.09	300.29	525.5	
ρ	0.75**	0.47**	0.34**	0.24**	0.17**	0.13**	0.11**	0.07**	0.06**	0.03	−0.01
σ_1^2	56.18%	15.54%	11.72%	7.26%	3.20%	2.02%	1.16%	0.64%	0.64%	0.15%	0.09%
σ_2^2	56.18%	15.54%	11.72%	7.26%	3.20%	2.02%	1.16%	0.64%	0.64%	0.15%	0.09%
						S.PBRICT					
μ	2.80	5.86	11.61	23.62	47.77	100.10	191.09	350.33	420.40	525.50	
ρ	0.75**	0.47**	0.33**	0.22**	0.16**	0.13**	0.09**	0.04*	0.02	−0.01	−0.01
σ_1^2	55.59%	20.55%	12.71%	5.43%	3.31%	0.03%	0.94%	0.33%	0.10%	0.02%	0.01%
σ_2^2	55.59%	20.55%	12.71%	5.43%	3.31%	0.03%	0.94%	0.33%	0.10%	0.02%	0.01%
						S.PEA					
μ	2.89	5.67	10.89	21.90	42.04	77.85	150.14	233.56	420.40	700.67	
ρ	0.62**	0.52**	0.41**	0.31**	0.19**	0.18**	0.11**	0.10**	0.08**	0.01	0.02
σ_1^2	55.59%	20.55%	12.71%	5.43%	3.31%	0.03%	0.94%	0.33%	0.10%	0.02%	0.01%
σ_2^2	55.59%	20.55%	12.71%	5.43%	3.31%	0.03%	0.94%	0.33%	0.10%	0.02%	0.01%
						S.PFBMIS					
μ	2.70	5.65	11.55	21.67	39.66	75.07	150.14	300.29	420.40	700.67	
ρ	0.74**	0.45**	0.33**	0.20**	0.15**	0.13**	0.10**	0.09**	0.06**	0.02	0.01
σ_1^2	54.98%	18.83%	12.02%	6.33%	2.43%	5.74%	2.98%	2.51%	0.58%	0.29%	0.07%
σ_2^2	54.98%	18.83%	12.02%	6.33%	2.43%	5.74%	2.98%	2.51%	0.58%	0.29%	0.07%
						S.PGBMI					
μ	2.79	5.77	11.06	19.64	34.46	63.70	116.78	191.09	350.33	525.50	
ρ	0.74**	0.48**	0.34**	0.25**	0.19**	0.15**	0.10**	0.05**	0.05*	0.04*	0.02
σ_1^2	54.48%	16.35%	10.22%	6.21%	4.35%	3.23%	1.74%	0.30%	0.27%	0.17%	0.04%
σ_2^2	54.48%	16.35%	10.22%	6.21%	4.35%	3.23%	1.74%	0.30%	0.27%	0.17%	0.04%
						S.PLABMI					
μ	2.75	5.43	10.41	20.02	35.63	70.07	123.65	262.75	350.33	700.67	
ρ	0.77**	0.49**	0.33**	0.22**	0.14**	0.14**	0.11**	0.07**	0.05*	0.03	−0.01
σ_1^2	55.70%	15.51%	9.93%	5.05%	3.80%	4.67%	1.43%	0.90%	0.30%	0.32%	0.01%
σ_2^2	55.70%	15.51%	9.93%	5.05%	3.80%	4.67%	1.43%	0.90%	0.30%	0.32%	0.01%

(*continued*)

Table S4.

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMFF9	IMF10	RESID
						S.PNA					
μ	2.78	5.62	10.95	21.67	42.04	87.58	150.14	210.40	300.29	700.67	
ρ	0.63**	0.50**	0.39**	0.25**	0.16**	0.13**	0.08**	0.09**	0.05*	0.03	0.01
σ_1^2	48.84%	24.30%	17.56%	8.56%	4.13%	3.35%	1.60%	1.47%	0.49%	0.20%	0.02%
σ_2^2	48.84%	24.30%	17.56%	8.56%	4.13%	3.35%	1.60%	1.47%	0.49%	0.20%	0.02%
						S.PPAFS					
μ	2.76	5.40	10.20	20.41	36.88	70.07	131.38	262.75	300.29	420.40	
ρ	0.68**	0.48**	0.36**	0.25**	0.17**	0.12**	0.12**	0.08**	0.08**	0.08**	0.04*
σ_1^2	53.04%	20.18%	12.90%	6.46%	4.92%	3.23%	2.62%	1.42%	0.10%	0.54%	0.30%
σ_2^2	53.04%	20.18%	12.90%	6.46%	4.92%	3.23%	2.62%	1.42%	0.10%	0.54%	0.30%
						S.PSSA					
μ	2.82	5.68	11.49	22.13	40.42	67.81	116.78	175.17	300.29	525.50	
ρ	0.68**	0.53**	0.35**	0.24**	0.20**	0.18**	0.14**	0.07**	0.06**	0.06**	0.03
σ_1^2	46.51%	22.67%	11.85%	6.80%	3.70%	3.39%	1.70%	0.37%	0.64%	0.47%	0.02%
σ_2^2	46.51%	22.67%	11.85%	6.80%	3.70%	3.39%	1.70%	0.37%	0.64%	0.47%	0.02%

Note(s): [*; **] show significance levels at 5 and 1%, respectively
Source(s): Table by authors

Table S5. Conventional equities (NASDAQ) measures of IMFs obtained through I-CEEMDAN

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	RESID
						NAMERICAI					
μ	2.73	5.24	10.25	18.44	32.84	61.82	116.78	210.20	350.33	420.40	
ρ	0.81**	0.40**	0.31**	0.19**	0.16**	0.13**	0.08**	0.03	0.02	0.03	0.02
σ_1^2	63.40%	12.85%	11.35%	3.96%	3.44%	2.77%	1.10%	0.23%	0.05%	0.08%	0.04%
σ_2^2	63.40%	12.85%	11.35%	3.96%	3.44%	2.77%	1.10%	0.23%	0.05%	0.08%	0.04%
						NAREITs					
μ	2.70	5.50	10.20	19.46	37.54	67.81	123.65	210.20	350.33	525.50	
ρ	0.78**	0.46**	0.23**	0.24**	0.15**	0.11**	0.08**	0.04*	0.04*	0.01	−0.01
σ_1^2	61.04%	19.44%	9.72%	8.36%	2.57%	1.26%	1.05%	0.25%	0.14%	0.01%	0.01%
σ_2^2	61.04%	19.44%	9.72%	8.36%	2.57%	1.26%	1.05%	0.25%	0.14%	0.01%	0.01%
						NASIAI					
μ	2.69	5.47	10.56	21.45	39.66	70.07	150.14	300.29	420.40	420.40	
ρ	0.72**	0.50**	0.37**	0.24**	0.17**	0.12**	0.10**	0.06**	0.03	0.01	0.01
σ_1^2	52.34%	20.97%	12.34%	7.46%	2.85%	1.30%	1.20%	0.30%	0.09%	0.02%	0.01%
σ_2^2	52.34%	20.97%	12.34%	7.46%	2.85%	1.30%	1.20%	0.30%	0.09%	0.02%	0.01%
						NBRICI					
μ	2.76	5.89	11.74	23.10	43.79	87.58	150.14	300.29	420.40	700.67	
ρ	0.75**	0.47**	0.37**	0.23**	0.16**	0.17**	0.08**	0.06**	0.03	0.01	−0.01
σ_1^2	55.19%	16.61%	11.46%	6.08%	2.34%	3.23%	0.66%	0.63%	0.26%	0.07%	0.01%
σ_2^2	55.19%	16.61%	11.46%	6.08%	2.34%	3.23%	0.66%	0.63%	0.26%	0.07%	0.01%
						NDMI					
μ	2.83	5.65	10.56	18.77	33.36	61.82	100.10	175.17	350.33	700.67	
ρ	0.75**	0.45**	0.36**	0.18**	0.16**	0.13**	0.10**	0.06**	0.05*	0.02	0.01
σ_1^2	57.23%	14.39%	12.15%	6.50%	6.60%	2.96%	2.10%	0.31%	0.44%	0.12%	0.04%
σ_2^2	57.23%	14.39%	12.15%	6.50%	6.60%	2.96%	2.10%	0.31%	0.44%	0.12%	0.04%
						NEMI					
μ	2.81	6.01	12.22	23.62	42.90	84.08	131.38	233.56	350.33	525.50	
ρ	0.74**	0.47**	0.36**	0.21**	0.19**	0.15**	0.13**	0.06**	0.05*	0.01	0.01
σ_1^2	53.96%	17.40%	11.69%	6.11%	3.22%	2.04%	2.04%	0.84%	0.81%	0.18%	0.05%
σ_2^2	53.96%	17.40%	11.69%	6.11%	3.22%	2.04%	2.04%	0.84%	0.81%	0.18%	0.05%

(continued)

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	RESID
						NEUROPI					
μ	2.74	5.62	10.72	19.28	36.88	65.69	105.10	191.09	350.33	700.67	
ρ	0.72**	0.45**	0.35**	0.24**	0.16**	0.12**	0.10**	0.60**	0.03	0.01	0.01
σ_1^2	58.16%	20.48%	12.05%	6.28%	2.79%	1.67%	1.16%	1.01%	0.49%	0.14%	0.07%
σ_2^2	58.16%	20.48%	12.05%	6.28%	2.79%	1.67%	1.16%	1.01%	0.49%	0.14%	0.07%
						NEUROZI					
μ	2.71	5.64	10.95	20.41	39.66	67.81	116.78	191.10	300.29	420.40	
ρ	0.73**	0.47**	0.37**	0.21**	0.17**	0.13**	0.09**	0.07**	0.05*	0.03	0.02
σ_1^2	55.73%	19.16%	12.88%	4.66%	4.35%	2.29%	1.44%	0.68%	0.16%	0.09%	0.01%
σ_2^2	55.73%	19.16%	12.88%	4.66%	4.35%	2.29%	1.44%	0.68%	0.16%	0.09%	0.01%
						NGMCI					
μ	2.75	5.45	11.12	19.64	38.93	80.85	131.38	262.75	420.40	700.67	
ρ	0.78**	0.44**	0.37**	0.24**	0.16**	0.12**	0.08**	0.06**	0.03	0.02	−0.01
σ_1^2	57.74%	13.67%	11.77%	6.03%%	3.19%	2.21%	0.70%	0.39%	0.21%	0.01%	0.01%
σ_2^2	57.74%	13.67%	11.77%	6.03%%	3.19%	2.21%	0.70%	0.39%	0.21%	0.01%	0.01%
						NGVOLNDX					
μ	2.94	5.50	10.72	20.61	34.46	56.81	87.58	161.69	262.75	525.50	
ρ	0.73**	0.41**	0.18**	0.10**	0.06**	0.01	0.01	0.01	0.01	−0.01	0.01
σ_1^2	77.94%	38.55%	14.70%	5.36%	2.90%	2.12%	3.42%	0.63%	0.01%	0.01%	0.01%
σ_2^2	77.94%	38.55%	14.70%	5.36%	2.90%	2.12%	3.42%	0.63%	0.01%	0.01%	0.01%

Note(s): [*; **] show significance levels at 5 and 1%, respectively
Source(s): Table by authors

Table S5.