Hindawi
Discrete Dynamics in Nature and Society
Volume 2022, Article ID 3938331, 28 pages
https://doi.org/10.1155/2022/3938331

Research Article

Situated Information Flow between Food Commodity and Regional Equity Markets: An EEMD-Based Transfer Entropy Analysis

Samuel Kwaku Agyei,[1] **Peterson Owusu Junior**,[1] **Ahmed Bossman**,[1] **and Emmanuel Yaw Arhin**[2]

[1]*Department of Finance, School of Business, University of Cape Coast, Cape Coast, Ghana*
[2]*Department of Accounting, School of Business, University of Cape Coast, Cape Coast, Ghana*

Correspondence should be addressed to Ahmed Bossman; ahmed.bossman@outlook.com

Received 7 March 2022; Revised 20 March 2022; Accepted 23 March 2022; Published 30 April 2022

Academic Editor: Stefan Cristian Gherghina

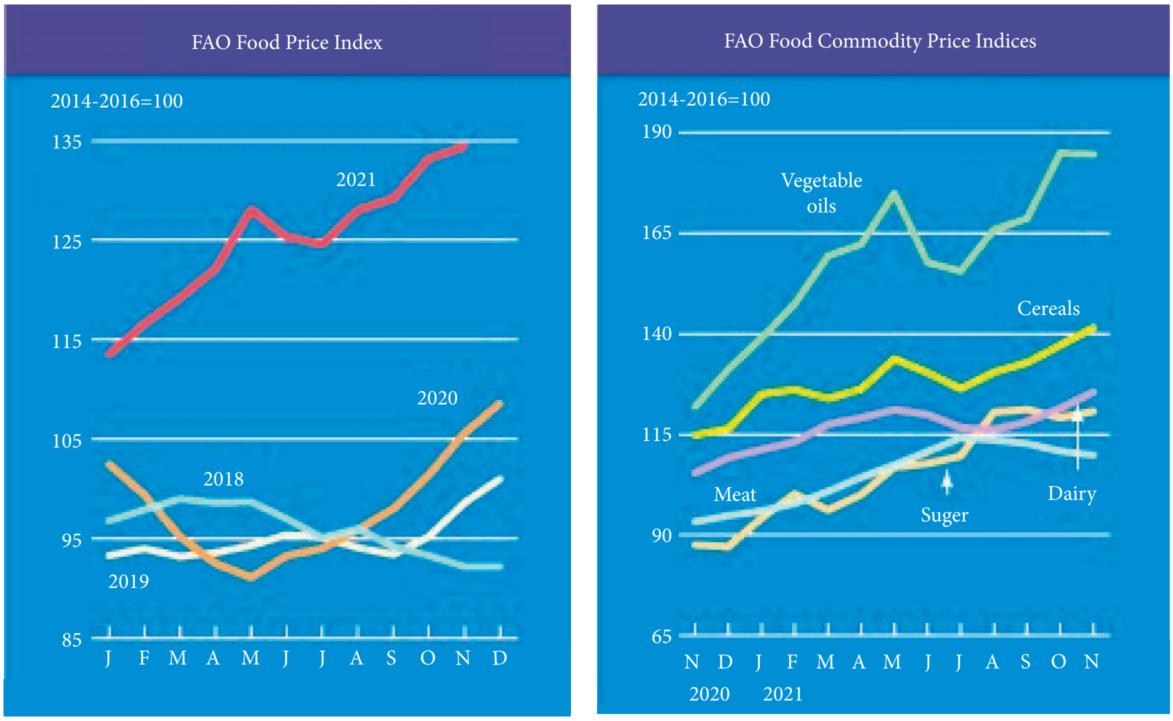
The intrinsic information shared by financial assets provides a means of assessing their mutual linkages. In times of crisis, spillovers and information flow between markets increase, and this drives empirical investigations into the degree of connectedness between financial assets. In the context of commodity markets, empirical evidence about the mutual information shared and its influence on portfolio management is largely unknown. This study examines the situated information between the food commodities (cereals, dairy, food, meat, vegetable oil, and sugar) of the FAO and regional stock markets' returns. From the ensemble empirical mode decomposition (EEMD)-based Rényian transfer entropy analysis employed, we find significant bidirectional information flow between the food commodities and regional equity markets. Our findings divulge that the diversification potentials of food commodities rest in the long term, with sugar being a consistent diversifier across all investment horizons. The investment and policy implications of our findings are further discussed.

1. Introduction

The markets for agricultural commodities have had a remarkable linkage with each other in recent years, with major swings and drastic changes. Agricultural commodity prices may fluctuate a lot; therefore, hedging against their negative fluctuations, for example, through futures markets, become a major and crucial responsibility for market players. Price volatility will not only drive anomalies in agricultural markets but also result in higher expenditure for exporters, importers, and individual customers. This makes the market unreliable because accurate economic forecasts of the future will be impossible, deterring both present and prospective investors [1, 2].

Food security for poorer households may be jeopardised by a major transmission of growing worldwide food prices [3], and volatility in these food prices may ultimately impact the poor, especially in countries with little or no agricultural warehouses [1]. It is worth emphasising that food price rises have not been uniform over the world and that these agonising increases in food costs have disproportionately impacted the poor, particularly in agriculturally reliant nations, where staple foods account for a major share of income [2].

Records from the Food and Agriculture Organisation (FAO) indicate that for almost over a decade, the food price index (FPI) of FAO reached its highest level in October 2021 and continued to increase in November 2021 [4]. A complete picture of the recent trajectories in the FPI and its constituent commodities is shown in Figure 1. FAO's FPI comprises indices of five key commodities, namely cereals, dairy, meat, vegetable oil, and sugar. The FPI is a monthly assessment of the change in worldwide food commodity prices consisting of 23 commodities and their subcategories.



(a) (b)

Figure 1: Trajectories of FAO indices for FPI (a) and its constituents (b) (source: FAO [4]).

The price movement in multiple commodities is tracked and endogenously determined by each of these indicators. The cereals price index, for example, reflects changes in worldwide wheat, maize/corn, and rice prices. This gives a broad spectrum for analysis.

These commodity indices have experienced historical trends in the COVID-19 era. For instance, FAO [4] reports that wheat prices rose for the fifth month in a row, reaching their highest level since May 2011. More recently, "the FAO Dairy Price Index averaged 132.1 points in January, up 3.1 points (2.4%) from December 2021, marking the fifth consecutive monthly increase, and placing the index 20.8 points (18.7%) above its value in the corresponding month last year" [5]. Several dynamics in the FAO FPI and commodity price indices have been witnessed since the emergence of the COVID-19 pandemic. On top of these revelations about food commodity prices, the United Nations Economic Commission for Africa (UNECA) [6] has cautioned against the persistence of volatilities in food commodity prices in the COVID-19 era. It is noteworthy that recent developments in food commodity prices are suggestive of their linkages.

One of the main reasons why returns and volatility in agricultural markets might be linked is that because economies are intertwined through trade and investment, any news concerning supply and demand in one country has ramifications for the others [7]. Hedgers and speculators in international markets, for example, are widely known for basing their judgments on information generated locally and from foreign markets [7, 8]. During the COVID-19 pandemic, spillovers and information flow between the markets—both commodities and equities—intensified [8, 9]. Furthermore, in recent decades, the increasing attention on commodity markets' financialisation has caused significant changes in some fundamental relationships between commodities and traditional assets such as stocks and bonds [10, 11]. From the above arguments, we propose that studies on commodities focus on a new direction that examines information flow between commodities and global equities to inform international portfolio management.

The sources of volatilities among food prices [12], the effect of market crises on food prices [1, 13, 14], comovement, and drivers of food price connectedness [3, 15] have been examined, but information flow has been left out. Specifically, information flow between food commodities and stock markets has not yet received scholarly attention. Nonetheless, the importance of this strand of empirical literature cannot be underestimated, as explained in the previous paragraphs. Theoretically, a measure of information vis-à-vis the driving and responding flow for multiple time-variant variables could be determined. Schreiber [16] defines this as transfer entropy (TE).

Based on the philosophical principles of Dretske [17] and Pearl's [18] statistics, the quantification of the intrinsic information flow between two random time series variables is made possible. This forms the foundation of the situated information flow theory (SIFT) [19]. The SIFT advocates that causality between financial markets could be retrieved from the common information they share. Consequently, if there is the mutual information between two random time series, their relationship could be inferred by analysing how the state of one of the variables is learnt by the other through observation [8, 9, 20–25]. In the context of this study, the dynamics in either market (commodity or stock) could influence the other. Therefore, a two-way flow, where stocks could observe the behaviour of commodities and vice versa through the commonly shared inherent information, is considered.

Furthermore, we propose that since economies are intertwined through investment and trade, any news concerning pricing, supply, and demand of commodities, together with news from the regulation of regional or national stock markets, have ramifications for the others [1, 7]. Financial market hedgers and speculators across the globe, for example, are widely known for making judgments based on both locally and internationally generated information [7, 26]. Thus, a quantification of the mutual information between these markets is important for policy management, asset allocation, risk-taking, and portfolio management. This influences the use of transfer entropy to examine the causal relationships between commodities and stocks in the global market space.

Notwithstanding, evidence from the empirical literature [8, 9, 20–25, 27] suggest that the flow of information and investor response to such information is not only time-dependent but also varies across frequencies. It is instructive to note that frequency-domain analysis is a significant component for investors who operate at different time horizons [28–37]. Moreover, the stylised facts of fat tails and volatility clustering of financial time series introduce the complexity, asymmetry, and nonlinearity in the behaviour of market participants [20, 34, 36, 38, 39]. Empirically, one sure way of catering for nonlinearity and asymmetry is through decomposition, which delineates observations into intrinsic time representing the short-, medium-, and long-term horizons. Consequently, in measuring the flow of information between commodity and stock markets, the right techniques need to be employed.

To cater for noise in the data series that may compromise the quantification of information transfer, we employ the ensemble empirical mode decomposition (EEMD) approach to demarcate observations into their inherent mode functions (IMFs), which are cyclicities that corroborate investment horizons [40]. The EEMD performs better and overcomes the limitations of approaches such as the Fourier and wavelet transforms and the empirical mode decomposition (EMD) [9]. In terms of transfer entropy, we employ the Rényi entropy (RE), which is a unique form of entropy capable of applying deserving weights to distinct tails of a given data series. The heavy tails contained in financial data sets are unaccounted for by the Shannon entropy [8, 9, 20, 24, 25]. Thus, the RE is appropriate.

We offer several contributions to the body of knowledge. First, we use the five essential FAO food commodity indices, which are rarely studied together in previous works. The use of the world food index and its constituents gives a broad spectrum for analysis as opposed to earlier works that focus on a few commodities or commodity classes like energy or agriculture [12, 41, 42]. The FAO and the UNECA have cautioned against persistent volatilities in food commodities in the past few months, and these volatilities, according to UNECA [6], are forecasted to remain in the uncertain periods of the COVID-19 pandemic. Thus, we contribute by examining the situated information flow between the returns on food commodity indices and regional and global stock indices, given that stock markets have also been volatile in recent periods [8]. It then becomes essential to analyse the diversification hedge and safe-haven potentials as well as policy implications across diverse time scales. Second, frequency decompositions provide a procedure for examining, at various time scales, how commodity and stock indices observe each other through mutually shared information. Through the frequency-domain analysis, economic agents and policy-makers modify, adjust, and adapt to policy actions conditioned on investment horizons.

Third, our study significantly differs from the recent extant studies that are largely limited around specific class(es) of commodity and/or stock markets. The extant literature contains works that focus on energy commodities [56, 60], the US or selected stock markets [42–44], or realised volatilities [59], etc. Whilst these works do not capture food commodities or fail to extend their sample period to the prevailing systemic risk, the quantification of the mutual information shared is completely missing in the case of world food indices. The dynamics between world food commodity markets are necessary to offer comprehensive insights on portfolio management across regional and/or market blocs. To contribute to the body of knowledge, this gap is abridged by this study through the analysis of the situated information between world food commodity and regional equity markets across the systemic risk of the COVID-19 era.

Fourth, with the stipulated indices, we employ a novel methodology, the EEMD-based transfer entropy, which is yet to be used in tandem with the studied variables. No existing study employs the selected FAO food indices together with regional and global stock indices and uses the Rényi transfer entropy approach. This is an addition to the empirical literature.

Furthermore, fat tails in financial time series, which are particularly powerful in exuberant trading periods, must be accounted for. Our data set covers essential turbulent trading scenarios such as Brexit, the trade tension between the USA and China, and the COVID-19 pandemic. These market stress periods render financial time series even more complex, nonlinear, and asymmetric [9, 25]. Consequently, the transfer entropy, as we employ in this study, offers a novel approach for quantifying causal effects that captures model-free information flow measurement, does not rely on the structure of the data or assumptions about linearity, and overcomes spurious linkages, making it a novel technique for basic causality paradigms such as the Granger causality test [46]. Thus, we examine the dynamic connectedness over the short-, intermediate-, and long-term horizons through the Rényi transfer entropy (RTE) technique.

Our findings suggest that the diversification potentials of cereals and dairy lie in the long term. For food, meat, and vegetable oil, the short- and long-term dynamics resulting from information flow produce diversification benefits for regional and/or global equity markets, whereas sugar provides diversification benefits across all investment scales.

The remainder of this study is structured as follows: Section 2 is dedicated to literature review; Section 3 discusses methods; Section 4 analyses the data and preliminary analysis; Section 5 presents empirical results and discussion; and Section 6 concludes the study.

2. Literature Review

In line with the broad literature on commodity markets, we present our review under the major strands of works in the extant literature as follows.

2.1. Return and Volatility Spillover Dynamics for Agricultural Commodities. The extant literature on food commodities has taken several directions with a new emerging strand that measures the intrinsic information flow between commodities. From the family of GARCH, earlier works focused on the volatility transmission between commodities.

Over the period 2003–2010, Lahiani et al. [47] investigate the return and volatility spillovers for four key agricultural commodities—sugar, wheat, maize, and cotton—using the VAR-GARCH. Their findings demonstrate that agricultural commodity returns and volatilities have significant volatility spillover links. When the GARCH models were employed on daily prices of eight main commodities (including crude oil, gasoline, barley, heating oil, maize, sorghum, and wheat), Mensi et al. [48] investigate the dynamic return and volatility spillovers between globally traded energy and cereal commodity markets and the effects of three different forms of OPEC news announcements on volatility spillovers and market persistence. Their findings divulge strong ties between the energy and grain sectors. Additionally, Mensi et al. reveal that OPEC news releases have an impact on the oil markets as well as the oil-cereal connection. The authors show that after accounting for OPEC announcements in these multivariate GARCH models, volatility persistence diminishes (increases) for crude oil and heating (gasoline) returns but mixed outcomes for the cereal markets.

Baldi et al. [49] study commodity financialisation and the progressive integration of commodity and financial markets and the extent to which stock market shocks affect commodity price volatility. The authors report that during the 2008 financial crisis, volatility spillover grew dramatically, indicating a growing interconnectedness between financial and agricultural commodity markets. Through the ARMA-GARCH model, Shahzad et al. [50] analyse how much oil impacts the pricing patterns of agricultural commodities including wheat, maize, soybeans, and rice under bearish and bullish market states. The authors find evidence of symmetry in the tail dependency between the studied commodities and asymmetry in the oil-to-agricultural-commodity spillovers, which become more intense during the financial crisis.

The price dynamics of a variety of worldwide staple foods and cash crop futures prices are investigated by Amrouk et al. [51] using a multivariate Copula-DCC-GARCH model and a rolling-sample volatility index to determine the direction of the volatility spillover for staple-cash commodity couples. The authors report that the strength of interaction fluctuates significantly over time but is typically positive and greater during the period 2007–2012, when commodity prices were high and financial markets were stressed. Śmiech et al. [12] examine the causes of food price volatility between corn, soybean, wheat, rice, US currency, crude oil, and SP500 futures with daily series data from January 4, 2000, to April 1, 2017. The authors use the generalised vector autoregressive framework in a rolling sample method and report that volatility spillovers change over time.

A new strand of literature that utilises methodologies from the family of wavelets was initiated. Živkov et al. [37] examine the multiscale dynamic interconnectedness between wheat, maize, soybean, oats, and rice, using the wavelet methodology. The authors reveal that shorter (longer) time horizons have low (strong) coherence regions, providing evidence in support of the concept of diversity. In the time-frequency domain, Tiwari et al. [52] examine the lead-lag connection between energy fuel price indices and food, industrial inputs, agriculture raw materials, metals, and drinks through the wavelet methodology with a data set spanning between 1990 and 2017. The wavelet coherency results show that the fuel and food prices, the fuel and industrial prices, and the fuel and metal prices all have major and significant relationships. With monthly data from 1997M1 to 2019M12, Frimpong et al. [3] use the wavelet techniques to explore the time-frequency influence of global EPU on the linkages between oat, rice, maize, wheat, and soybean. The authors reveal variation in linkage patterns of the agricultural commodities market at different scales of time and frequency, which is particularly pronounced at low scales.

2.2. Commodity Markets, Information Flow, and Systemic Risks. The recent strand of literature encompasses studies that examine the information flow between commodities. Using the transfer entropy approach, da Silva et al. [53] investigate the path of information flow between Brazilian ethanol and sugar prices and global crude oil prices. For the return and volatility series, da Silva et al. found stronger information transfer from crude oil to sugar and crude oil to ethanol, but for the original series, the net information transfer was in the reverse direction. Caglar and Hancock [54] look at how to infer networks containing time series data and how to characterise information flow across time series using two distinct information-theoretic methods. The first employs Jensen-Shannon divergence to quantify network similarity and uses transfer entropy to characterise information flow. The second method compares the distribution of correlations across edges for different networks using time series correlation and Kullback–Leibler divergence.

Huynh [46] takes a look at the causal link between precious metals prices and uncertainty, as assessed by the two proxies: Economic Policy Uncertainty (EPU) and the Chicago Board Options Exchange Volatility Index (CBOE-VIX). Huynh evaluates data for gold, silver, palladium, and platinum using two cutting-edge methodologies: multilayer perceptron neural network nonlinear Granger causality and transfer entropy. The author finds that gold remains the most popular safe-haven asset for hedging against risk. The studied precious metals were also shown to influence EPU and VIX, although they are resistant (unresistant) to EPU (VIX) shocks.

Huynh's study not only adds to a growing body of literature by introducing new quantitative methodologies reinforced by neural networks and econophysics but also sheds light on shock transmission mechanisms in commodity markets. A new strand of literature focusing on transfer entropies [55, 56] emerges in the body of knowledge. Under the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) paradigm, Niu and Hu [55] combined the transfer entropy from information theory with the multiscale analysis to measure the information transfer between the Chinese stock market and commodity futures. The authors find heterogeneous interrelations between the stock markets and the agricultural commodity futures, energy, and metals markets. Liu et al. [55] investigate international commodity price interactions from the standpoint of information transmission through a transfer entropy network hinged on empirical mode decomposition. At various time scales, the authors show that as time passes, the network transmission structure and core varieties alter. The authors find metals (energy) to have the highest transmission intensity in the near (medium- and long-run) term(s).

Through an asymmetric methodical framework, Rehman et al. [57] investigate the portfolio prospects and implications for energy and nonenergy assets with data in weekly frequency from 2010M1 to 2018M6. The long-run effect of oil price shocks on metal commodities was revealed. Wheat was the only food commodity considered in their study. The dynamics between other food commodity markets are necessary to offer comprehensive insights on portfolio management. The dynamic interrelations between commodity futures (i.e., crude oil and gold) and stock market returns from the USA, China, Germany, France, and Japan were analysed by Mezghani et al. [58] under the BEKK-GARCH and the Diebold–Yilmaz spillover connectedness frameworks. Their study was limited to gold and oil, with no evidence of how the returns from the studied stock markets comove with the returns from global food commodities.

Among strategic commodities and the US stock markets, Bouri et al. [43] examine the spillover dynamics with data spanning from April 11, 2006, to April 29, 2019. Whilst the significance of this study cannot be overlooked, the period does not cover the systemic risk era of COVID-19. Besides, these dynamics were not investigated for food commodity markets. Between national stocks and global commodity prices, Enilov et al. [44] examine their linkages with a mixed-frequency vector autoregression approach with weekly and monthly data sets covering the period 1951M1 and 2018M3. Aside from not covering the COVID-19 era, the peculiarities between stock markets and global food commodity indices were not considered by their study.

With the dependence parameter copula, Karakaş et al. [45] examine the vine copula interdependence structure of commodity and stock markets, limiting their scope to stock markets of the USA, Turkey, and the UK, and the only food commodity considered was soybean, whilst the study period (2017–2019) fails to incorporate an essential systemic crisis period, the COVID-19 pandemic. Recent works that forecast volatility dynamics between commodities provide no insights on global food commodities (see, e.g., [59]). As Iqbal et al. [60] incorporate agricultural commodity futures in their modelling of tailed risk dependence of commodity markets, it paves way for assessments of the intrinsic information content that is mutual to various commodity markets. As we find that the existing studies either do not capture food commodities or fail to extend their sample period to the prevailing systemic risk, this study seeks to overcome the empirical gap in the area of food commodity and regional stock markets by assessing the situated information flow common to global food commodity and regional stock market returns using the transfer approach, which was recently used in the context of energy markets by Ferreira et al. [61].

2.3. Motivation. From the extant literature, thus far, empirical evidence on the intensity and flow of intrinsic information flows food commodities is lacking. Frimpong et al. [3] documented that sudden shifts in policy uncertainty have a propensity to affect commodity price comovement, which puts the agricultural commodities market's stability in danger, necessitating policymaker involvement to prevent a spillover risk contagion effect in uncertain times. At this time when food price volatilities are intense and projected to continue in the period of the COVID-19 pandemic [4, 6], an assessment of the intrinsic information flow—situated on mutual policy actions and uncertainties—between food commodities is essential to influence effective policymaking and portfolio risk management. Furthermore, as documented by Shahzad et al. [50], increases in agricultural commodity prices have the potential to affect not just social and economic costs but also education, family, and health relationships owing to economic policy actions and uncertainties [3].

Therefore, to complement the emerging strand of works in the literature, we employ the transfer entropy technique hinged on decomposed data series to estimate the frequency-domain information flow between global food commodity markets. Our study is linked with the work of Hanif et al. [15] study in terms of the studied commodity indices. Hanif et al. consider the nonlinear relationship dynamics and risk spillovers between oil prices and global food prices, proxied by the world food price index and its subcategories: dairy, cereals, vegetable oil, and sugar. Employing the same set of food commodity indices together with regional equity markets, we add to the extant literature by quantifying the intrinsic information between these assets in the frequency space, which caters for nonlinearity, asymmetry, and heterogeneity of market participants, to assess the diversification benefits for portfolios containing these food commodities amid their rapid financialisation in recent decades [10, 11].

The heterogeneous markets hypothesis of Müller et al. [62] suggests that market participants make investment decisions across distinct time (investment) scales after adjusting their risk/reward preferences. Therefore, considering the persistent volatilities in the FAO commodity prices and the consequences of excessive capital injections towards commodity financialisation [63–66], we maintain that this study is timely.

3. Methods

Our methodical approach is in two steps. In the first, we use EEMD to extract intrinsic mode functions (IMFs) from the food commodity and stock returns, and in the second, we estimate transfer entropies with the IMFs as inputs. Given the nonlinearity and nonstationarity within and among our time series variables, IMFs are essential in this research since they reflect various time scales of the original time series [67]. In the context of commodity markets, recent works (see, e.g., [43, 57, 59, 60]) have also underscored nonlinearity and asymmetries in their cross-market linkages and spillovers. This means that analysing the information transfer between the sampled markets across various scales is essential.

3.1. Ensemble Empirical Mode Decomposition (EEMD). An advanced version of the EMD-induced signal processing approach is provided by the EEMD, which corrects for the effect of mode-mixing associated with the EMD. We carefully follow Wu and Huang's [68] procedures to summarise the EEMD algorithm as follows.

Generally, $y(t)$ is the aggregate of the actual data known as the signal $\alpha(t)$ and noise $(n(t))$, so that

$$y(t) = \alpha(t) + n(t). \tag{1}$$

Next, we generate from equation (1), i^{th} as a calculated observation, $y_i(t)$, in equation (2), by appending a white noise of various realizations, $\omega_i(t)$, which eradicates mode mixing and yields a consistently sound reference scale distribution to facilitate empirical mode decomposition.

$$y_i(t) = y(t) + \omega_i(t). \tag{2}$$

Thus, following Huang et al. [40], we generate the EEMD in four specific summarised stages:

Stage 1. Get $y_i(t)$ through the addition of white noise to the main data

Stage 2. $y_i(t)$ is decomposed into its inherent functions

Stage 3. The outputs from the first two stages are iterated with fluctuating series of white noise

Stage 4. The ensemble averages of linked IMFs of the decomposition are finally generated

The "libeemd" package of Luukko, Helske, and Räsänen [69] from R programming is used for these processes to develop the EEMD for this study.

3.2. Rényi Transfer Entropy. Transfer entropy is a consequence of Hartley's [70] general information theory. The quota of possible symbolic series in a given probability distribution is used to compute the quota of possible symbolic series in a given probability distribution [71, 72]. As an uncertainty measure, modern studies on TE employ Shannon's [73] arithmetical communication theory, which is gleaned from theoretic information.

The average symbolic information for a probability distribution having distinguishable symbols of a particular experiment P_j is expressed as follows:

$$H = \sum_{j=1}^{n} P_j \log_2\left(\frac{1}{P_j}\right) \text{bits}, \tag{3}$$

where n is the quantity of differing symbols associated with probability p_j [70]. The average number of bits necessary for optimal encoding autonomous draws may be estimated with Shannon's [73] paradigm (i.e., Shannon entropy (SE)) for a discretised random variable J with $p(j)$ probabilities.

$$H_J = -\sum_{j=1}^{n} p(j) \log_2 p(j). \tag{4}$$

Given two Markov time series procedures, a quantification of information flow between them is made with Kullback and Leibler's [74] distance model (KLDM). Let I, with marginal probability $p(i)$, and J with marginal probability $p(j)$ represent two discrete random time series. Their joint probability is then defined as $p(i, j)$. At order k (process I) and I (process J), we also assume dynamic stationarity for the Markov process. As stated by the Markov property, the probability at which I is observed in state i and time $t+1$ conditioned on k preceding data points is $p(i_{t+1}|i_t, \ldots, i_{t-k+1}) = p(i_{t+1}|i_t, \ldots, i_{t-k})$. The mean bits needed for encoding the data point at $t+1$ prior to knowing k observations are given as follows:

$$h_j(k) = -\sum_i p\left(i_{t+1}, i_t^{(k)}\right) \log_2 p\left(i_{t+1}|i_t^{(k)}\right), \tag{5}$$

where $i_t^{(k)} = (i_t, \ldots, i_{t-k+1})$ (correspondingly for process J). Information flow to I from J is examined in a bivariate case by quantifying the variance from the Markov property $p(i_{t+1}|i_t^{(k)}) = p(i_{t+1}|i_t^{(k)}, j_t^{(I)})$, as hinged on the KLDM. SE is then expressed as follows:

$$T_{J\longrightarrow I}(k,l) = \sum P\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right) \log \frac{P\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}{P\left(i_{t+1}|i_t^{(k)}\right)}, \tag{6}$$

where $T_{J\longrightarrow I}$ aggregates the information flow towards I from J. Analogously, the flow of information to J from I, which is $T_{J\longrightarrow I}$, can be obtained. The net estimate of information flow is computed as the excess of $T_{J\longrightarrow I}$ over $T_{J\longrightarrow I}$, which serves as the central information flow path.

The expediency of SE in the area of finance cannot be overemphasised, but it does not attribute equal weights to all probable expectations in a probability distribution. Note that fat tails are pervasive in asset pricing, but SE does not overcome this assumption. Therefore, we resort to Rényi's [75] transfer entropy, which uses a weighting value q, to overcome the shortfall of SE. RTE is computed as follows:

$$H_J^q = \frac{1}{1-q}\log_2 \sum_j P^q(j), \tag{7}$$

with $q > 0$. For $q \longrightarrow 1$, RE and SE converge. For $0 < q < 1$, more weight is assigned to low probability events, while for $q > 1$, outputs j with higher initial probabilities are favoured by the weights. Resultantly, based on q, RTE facilitates the assignment of different weights to unequal regions of the distribution [20, 25, 71]. This feature of RTE makes it superior over SE and, hence, its desirability in finance.

The companion distribution $\varnothing_q(j) = (p^q(j)/\sum_j p^q(j))$ for $q > 0$ is applied to normalise the weighted distributions [76], from which RE is estimated as follows:

$$RT_{J\longrightarrow I}(k,l) = \frac{1}{1-q} p\left(i_{t+1}, i_t^{(k)}, j_t^{(I)}\right)\log_2 \frac{\sum_i \varnothing_q\left(i_t^{(k)}\right)P^q\left(i_{t+1}|i_t^{(k)}\right)}{\sum_{i,j}\varnothing_q\left(i_t^{(k)}, j_t^{(I)}\right)P^q\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)}. \tag{8}$$

Note that negative estimates could be provided by the RTE. Noting the history of J, in this case, suggests significantly extra uncertainty than noting the history of I only would imply. Negative (positive) estimates depict higher (lower) risks in this context.

TE estimations are subject to biases in small samples [77]. The effective transfer entropy (i.e., ETE) can resolve this and is derived as follows:

$$ETE_{J\longrightarrow I}(k,l) = T_{J\longrightarrow I}(k,l) - T_{J\,\text{shuffled}\longrightarrow I}(k,l), \tag{9}$$

where the TE using faltered forms of the data series J is represented as $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$. The procedure removes the data series' serial reliance of J, whilst the statistical linkages amid J and I are preserved through repetitive random draws from the given return series J and rearranging them to produce a fresh return series. $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$ is therefore caused to approach zero as the sample size increases; nonzero values of $T_{J\,\text{shuffled}\longrightarrow I}(k,l)$ are caused as a result of biases with a small sample. Consequently, recurrent shuffles and the average of the shuffled TE estimates across all replications could be employed as an estimator of few sample biases, from which the derivation of bias-corrected ETE estimates is gotten after being deducted from the RE or SE estimates.

To establish the statistical significance of ETEs, the Markov block bootstrap technique is adopted. This process retains the dependencies within the variables J and I but eliminates their statistical linkages as opposed to shuffling. Resultantly, in line with the H_0 of "no information flow," a distribution of TE estimates is retrieved by bootstrapping. $1-\widehat{q}$T provides the accompanying $p-$ value, while $\widehat{q}$T offers a specification of the quantile of the simulated distribution produced by the relevant TE estimations (see [8, 71]).

4. Data and Preliminary Analysis

Our data set includes monthly indices on the aggregate world food commodity index and its constituents including cereals, dairy, meat, vegetable oil, and sugar and 11 regional NASDAQ equity indices for Asia, Asia-Pacific, BRIC, developed markets, emerging markets, Europe, Eurozone, global market, Latin America, the Middle East and Africa, and North America. The data set spans from December 2012 to September 2021. The world food commodity indices are provided by FAO and are available in monthly periodicities, and the equity indices are supplied by EquityRT. A trajectory of the commodities and regional equity indices' returns is presented in Figure 2.

At a glance, the return series suggests high volatilities in all indices, with high intensity in 2020/2021. For the studied food commodity indices, we spot drops in returns, with sugar and vegetable oil experiencing the sharpest drop in the COVID-19 era. A similar observation is made for the aggregated indices, the food price index, suggesting that aggregated losses are higher for food commodities in the studied COVID-19 period. For the studied regional equity markets, intense volatile clusters are found in the COVID-19 period with the global market index being an exception. This exception suggests that the aggregated impact of COVID-19 on global indices may not be felt, as extreme negative returns may be offset by extreme positive returns. Notwithstanding, over the studied period, the worse return on the global market index is spotted within 2016, which falls within a key incident, Brexit. The descriptive summary of the studied indices is presented in Table 1.

The descriptive statistics suggest that except for cereals, the returns on all other food commodity indices witnessed a positive mean over the studied period. Sugar and vegetable oil were found to have the highest return deviations, substantiating why the two indices had the sharpest drop in returns. Except for Latin America, all regional equity markets realised positive mean returns over the period. The studied commodity indices (equities) supported (rejected) normality, as indicated by the Normtest.W statistics. These statistics reignite the essence of this study.

5. Empirical Results and Discussion

This section presents and discusses the study's principal objective. The bidirectional intrinsic information flow between food commodities and regional equity markets is examined. The Rényian entropy approach generates both

Table 1: Descriptive summary.

Commodities/equities	Min.	Max.	Mean	SD	Skewness	Kurtosis	Normtest.W
Agricultural commodities							
Food	−0.0458	0.0480	0.0005	0.0200	0.0132	−0.4582	0.9920[(a)]
Meat	−0.0563	0.0471	0.0005	0.0205	−0.2722	−0.1107	0.9915[(a)]
Dairy	−0.0891	0.1055	0.0000	0.0344	−0.0522	0.6144	0.9808[(a)]
Cereals	−0.0734	0.0721	−0.0009	0.0294	0.0839	−0.2119	0.9933[(a)]
Veg. oil	−0.1328	0.1355	0.0034	0.0482	0.0312	0.1012	0.9873[(a)]
Sugar	−0.2125	0.1596	0.0001	0.0628	−0.2362	0.8326	0.9870[(a)]
Equities							
Asia	−0.1202	0.0927	0.0049	0.0366	−0.5413	1.0122	0.9731
ASPA	−0.1370	0.0977	0.0044	0.0378	−0.6146	1.4487	0.9688
BRIC	−0.2109	0.1410	0.0021	0.0518	−0.5932	1.8435	0.9715
Developed markets	−0.1519	0.1225	0.0080	0.0387	−0.6964	2.7251	0.9441
Emerging markets	−0.2146	0.1205	0.0021	0.0468	−0.8090	3.1257	0.9561
Europe	−0.1696	0.1580	0.0036	0.0444	−0.3446	1.9532	0.9670
Eurozone	−0.1958	0.1870	0.0046	0.0501	−0.2644	2.2892	0.9640
Global market	−0.2668	0.1148	0.0059	0.0651	−1.1270	1.8427	0.9285
Latin America	−0.4486	0.1970	−0.0045	0.0813	−1.2941	7.0333	0.9114
Middle East and Africa	−0.2773	0.1125	0.0001	0.0580	−0.9663	3.4944	0.9430
North America	−0.1536	0.1236	0.0104	0.0397	−0.7520	2.8274	0.9395

Notes. This table presents the descriptive statistics of the world food commodity and global equity indices' returns. Panel A presents the descriptive statistics for the world food indices, and Panel B presents the descriptive statistics for the regional equities. Veg. oil – vegetable oil and SD – standard deviation. [(a)] Significance at 1%.

negative and positive effective transfer entropies (ETEs). Negative ETEs represent high risk while positive ETEs indicate low risk. We conduct our analysis from the perspective of portfolio diversification. Among equities, diversification is permitted when negative ETEs recipients are paired with positive ETEs recipients, whereas between commodities and equities, diversification is possible with equities that negatively respond to shocks from (to) commodities (equities). Per the stylised facts of the financial data series, we account for fat tails in the return series by specifying a fault weight of 0.30. We present our results in both the composite and frequency domains. IMFs 1–5 and residual are used in the latter to show intrinsic times corresponding to short-, mid-, and long-term characteristics. The residual embodies the long-term path and reveals the fundamental character of the particular commodity and equity series. Using time scales, we assess one market's (food commodity indices') dynamic reaction to the other (regional equity markets) based on the situated information mutual to the markets.

At the composite (frequency-domain) level, black specks inside red (blue) bars indicate ETEs. The ETEs are depicted in the composite state in Figure 2 and the frequency-domain states in Figures 3–6. The 95% confidence bounds are located at the ends of the red or blue bands. As a result, we must reject the null hypothesis of "no information flow" if these confidence boundaries are in the positive or negative portions. Confidence bounds overlapping at the origin connote insignificant information flow. In Table 2, the ETEs in Figures 3–6 are numerically given.

5.1. Composite ETEs. We analyse the composite ETEs between the returns on world food commodity indices and regional equity markets. The ETE plots in Figure 3 are for cereals, dairy, food, meat, vegetable oil, and sugar. We analyse the ETEs for the various commodity markets in turn.

At the composite level, from Figure 3, we find that when shocks are present in food commodity markets, all regional equity markets respond negatively, but the aggregate response to such shocks is positive, which is evidenced by the positive ETE for the global market index. This observation reiterates the fact that the aggregated impact of COVID-19 on global indices may not be felt, as extreme negative returns may be offset by extreme positive returns. These ETEs, however, are insignificant. Conversely, aside from North American equities that transmit significant negative flow towards cereals, all other ETEs from equities towards cereals are insignificant.

No significant ETEs are found for ETEs towards equities, but equities from Asia, Eurozone, North America, and developed markets transmit positive (low-risk) ETEs towards dairy. For the food price index (FPI), Latin American stocks receive positive ETEs, while all ETEs both from FPI and equities are insignificant. For meat and vegetable oil, no significant ETEs are found. ETEs from sugar to equities were all positive with Global, Asia-Pacific, developed markets, and the Middle East and Africa being significant. Stocks from North America, developed markets, BRIC, and the Middle East and Africa transmit positive flows towards sugar, whereas global stocks transmit a negative flow.

At this point, it is essential to note that at the composite level, the only diversification prospect between equities amid commodity markets is that of global stocks against North America, developed markets, BRIC, and the Middle East and Africa. It is equally important to note that despite being highly risky, negative ETE recipients provide potential diversification to the commodity or equity market in question based on flow towards equity and commodity markets,

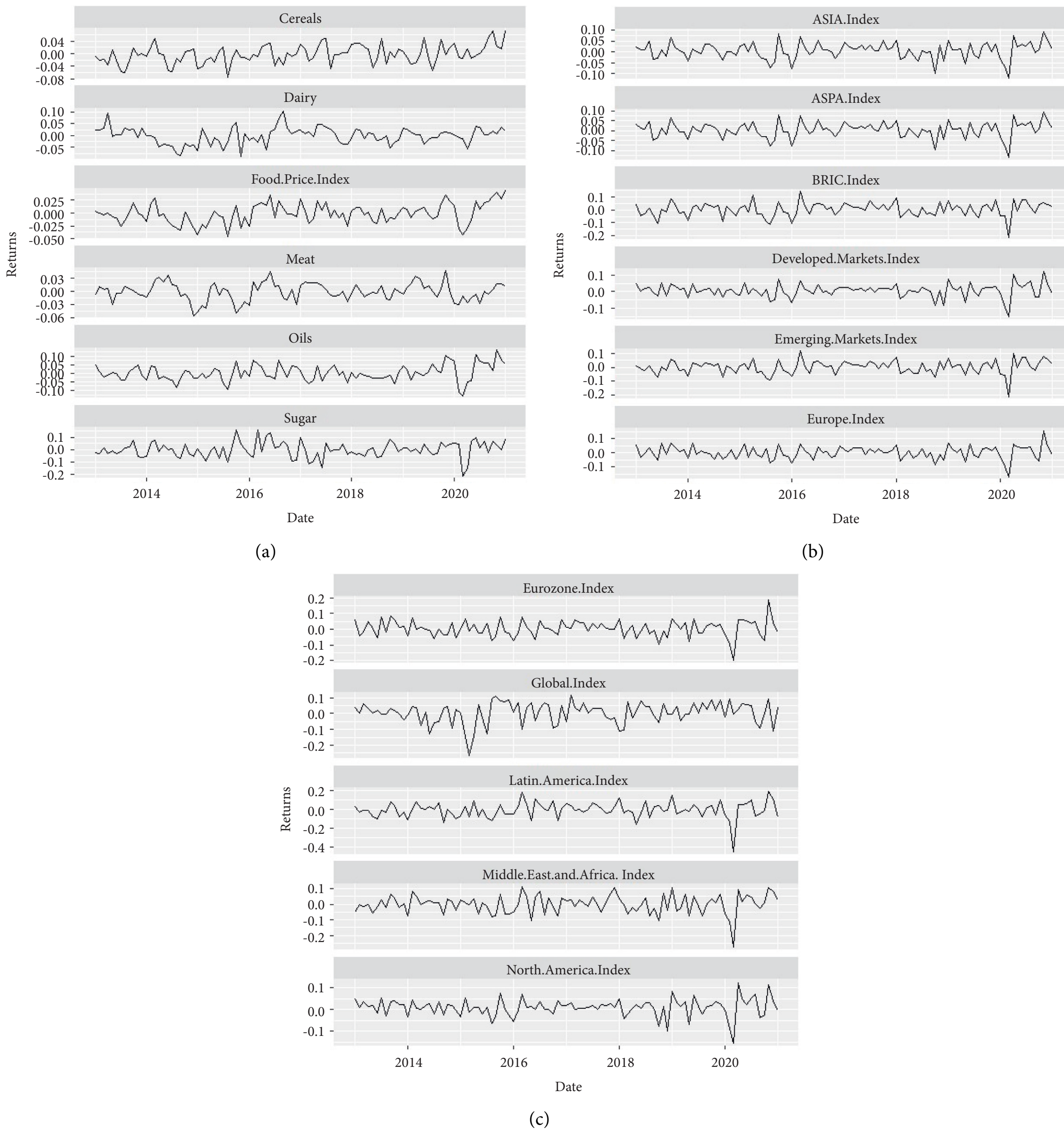


Figure 2: Time series plots of food commodity indices.

respectively. To provide evidence in the frequency domain, which are particularly of interest to short-, medium-, and long-term investors [8, 9], we turn to the frequency-domain ETEs.

5.2. Frequency-Domain ETEs. Just like the behaviour of market participants, commodity markets are noted to be heterogeneous [43, 57, 60, 78, 79]. Besides, given the fat tails embedded in financial time series, it is essential to delineate the return series into time horizons that correspond to investment terms of short-, medium-, and long-term periods. Following existing works [8, 9, 25], we attribute IMF1 and IMF2 to the short term, IMFs 3–5 to the intermediate-term, and IMF Residual to the long term. The short-, medium-, and long-term horizons are defined by Yang et al. [80] to be characterised or driven by investor sentiments and microstructure of the market, the significance of key events, and fundamental dynamics, respectively. We discuss the ETEs following the delineated investment horizons.

In the short term (Figure 4), we find no diversification potential from the ETEs. However, there are significant ETEs that need to be singled out. At IMF1, the global equity market receives (transmits) positive information flow from (to) cereals. Thus, cereals and global stocks are less risky to each other in terms of the mutual information they share. Stocks from Asia (the Middle East and Africa) transmit significant flow to the dairy (food) market. For information

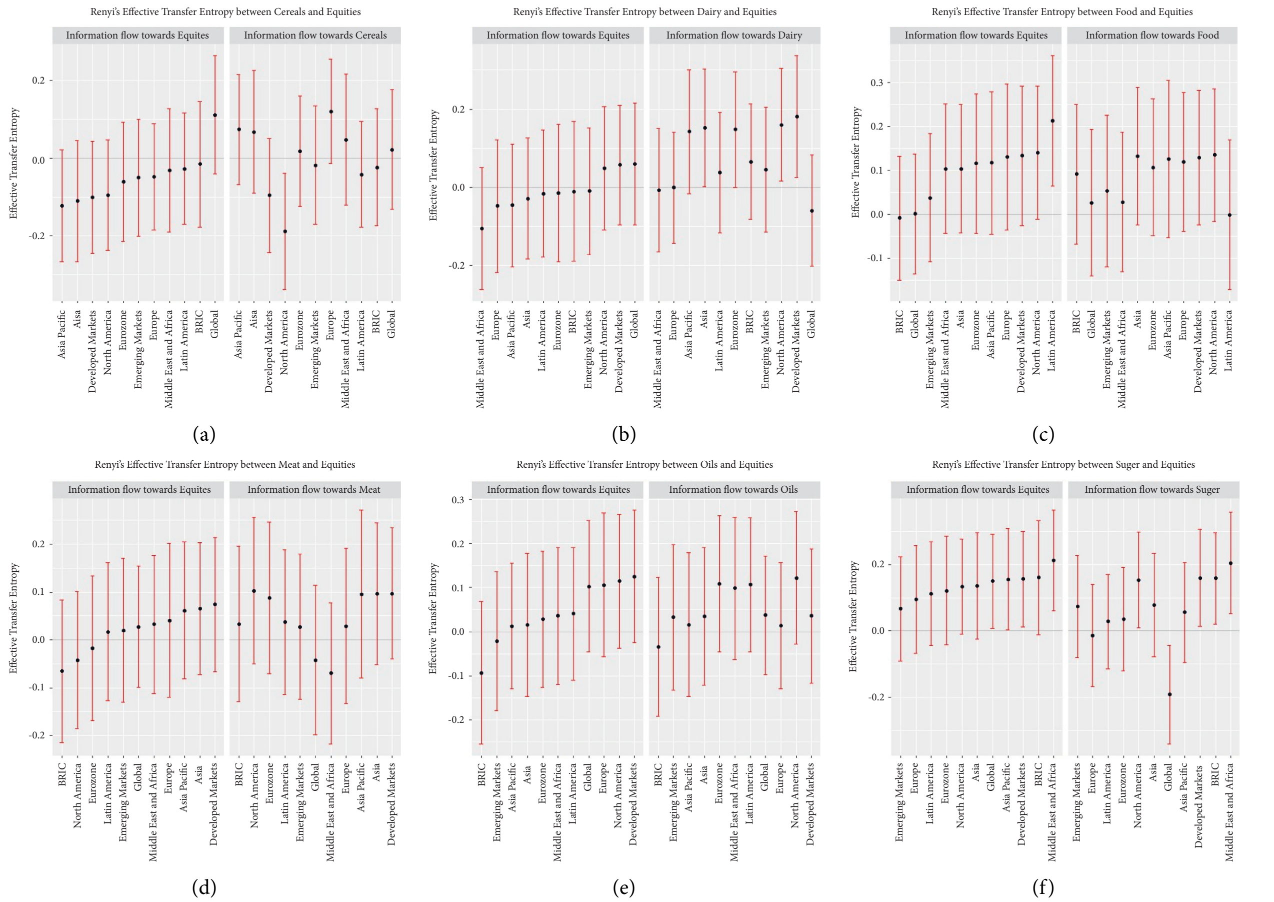


FIGURE 3: Transfer entropies at the composite level. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets for the signal/composite data. (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities.

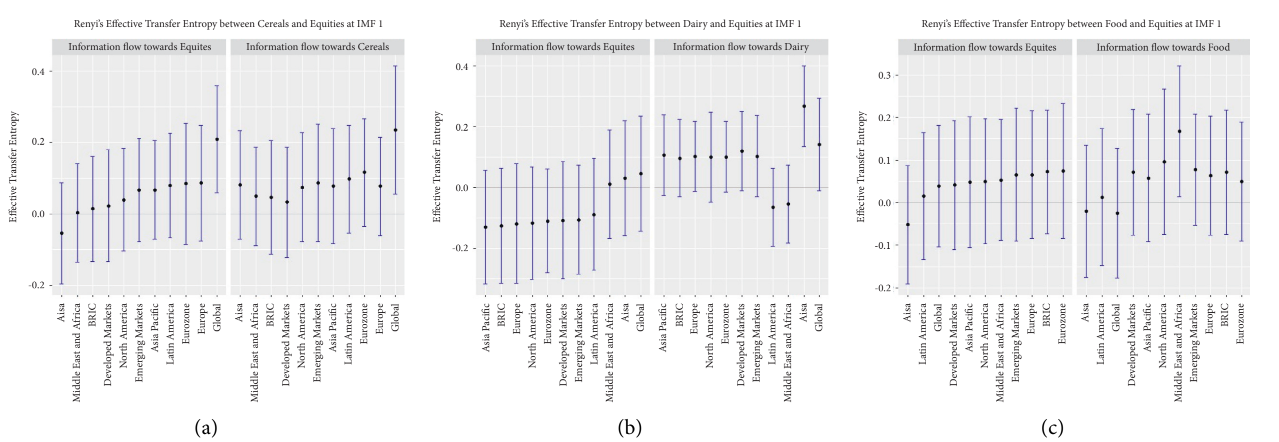


FIGURE 4: Continued.

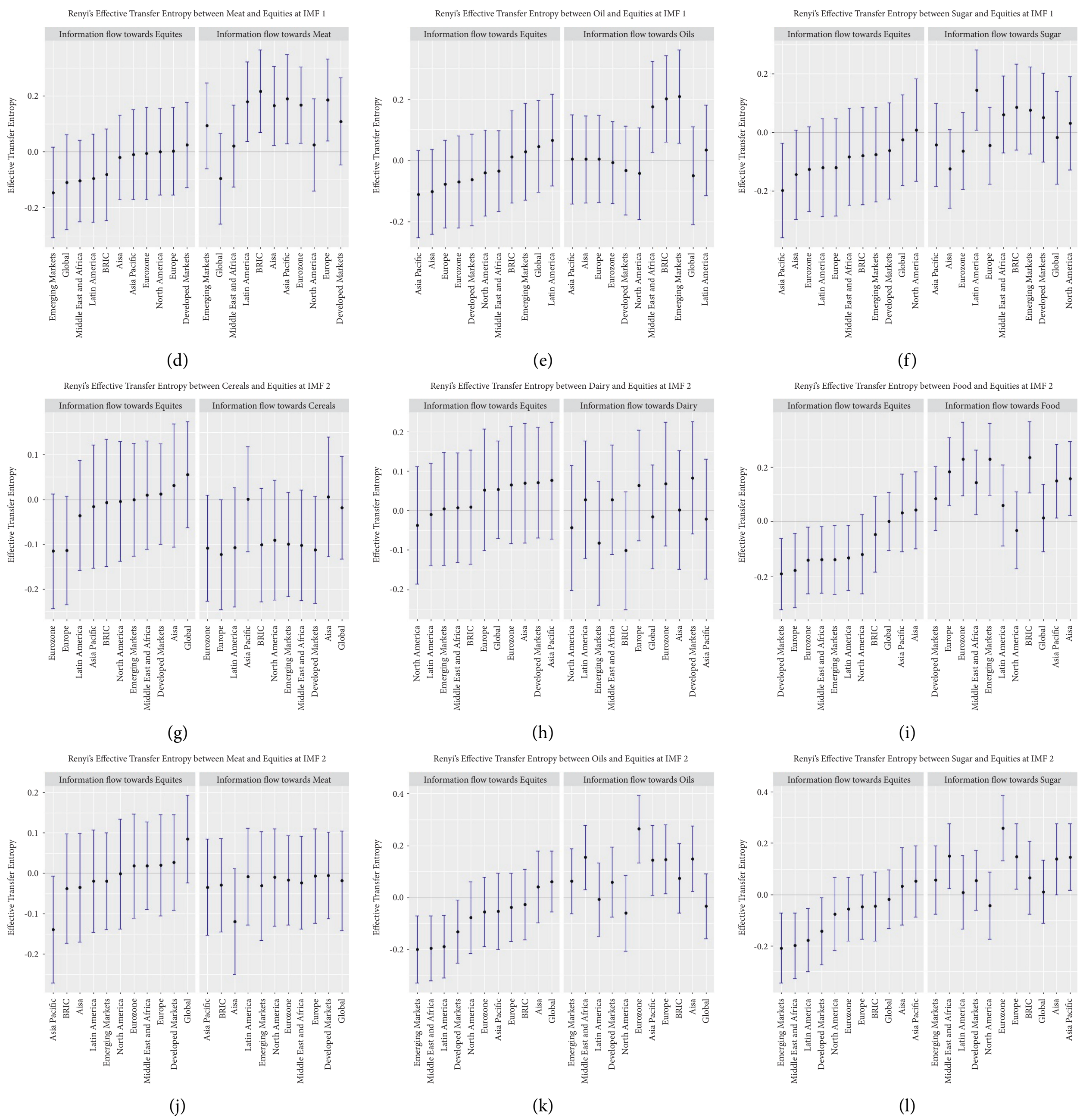


Figure 4: Transfer entropies in the short term. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets at short-term scales (IMFs 1 and 2). (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities for IMF1 with their corresponding IMF2 being (g) to (l).

flow towards vegetable oil, the Middle East and Africa, BRIC, and emerging markets transmit positive ETEs. Sugar transmits a negative information flow to Asia-Pacific stocks, suggesting that when contained in a portfolio, sugar could diversity with Asia-Pacific stocks when they are affected by commodity market shocks, but not vice versa. Latin American equity markets transfer a positive flow towards sugar.

At IMF2, equity of developed markets, European, Eurozone, Middle East and Africa, emerging markets, and Latin America receive negative ETEs from food. Thus, when the food market experience shocks, they are well diversified by the inclusion of stocks from the aforementioned markets. However, no diversification among equities is significant. Except for the equity markets of developed markets, Latin and North America, and Global markets, all other regional equity markets transmit positive information flow towards the food market. Asia-Pacific stocks are negative ETE recipients from the meat market. In both vegetable oil and sugar markets, emerging markets, Middle East and Africa, Latin America, and developed markets are negative ETE recipients, which suggests their potential as possible

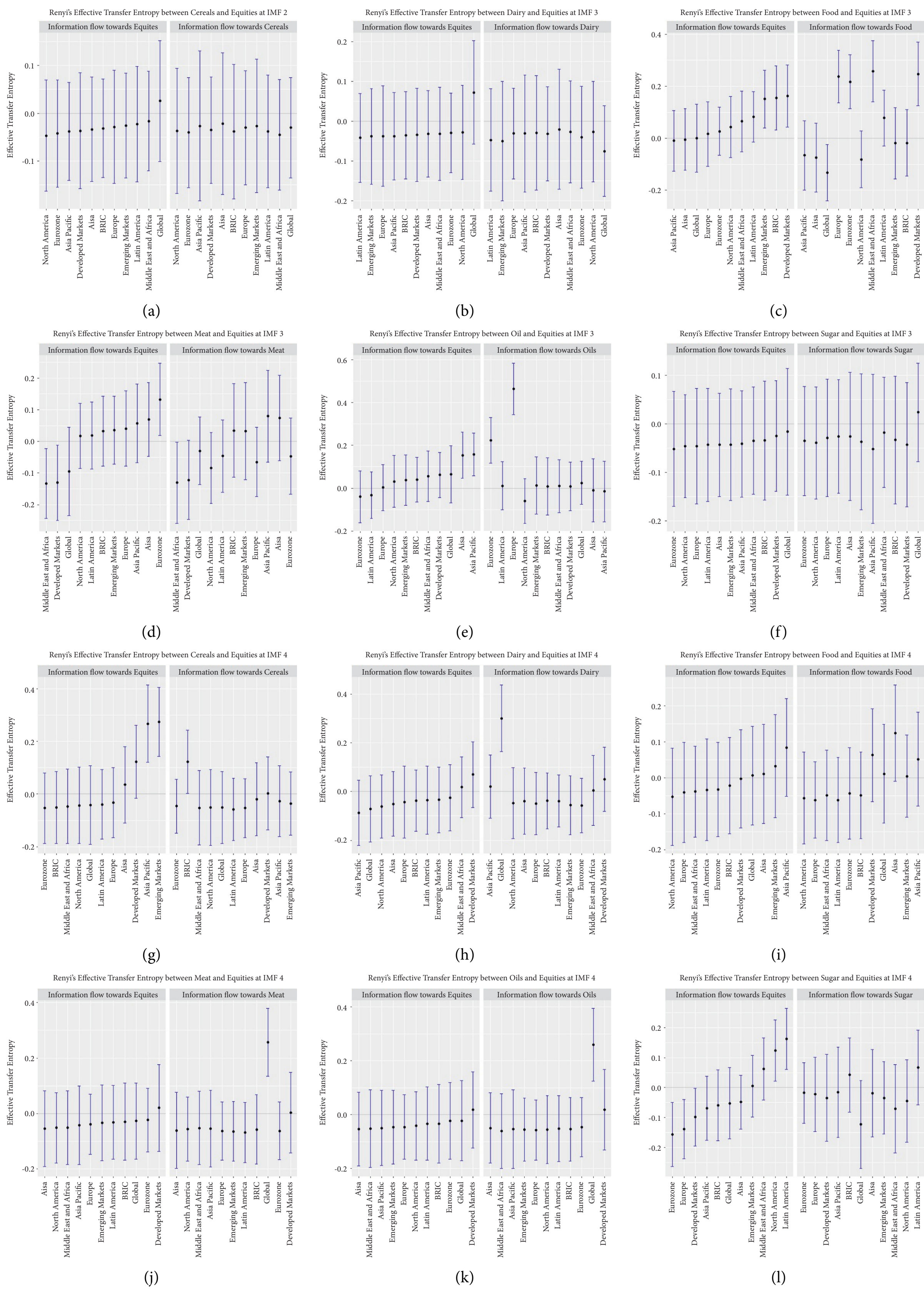
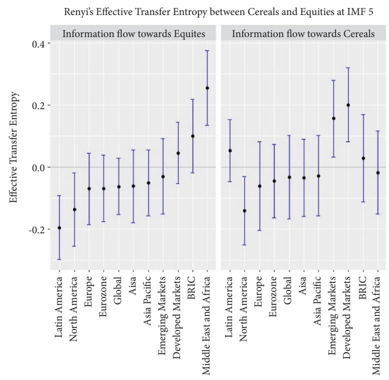
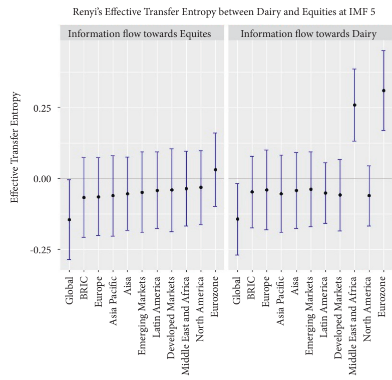


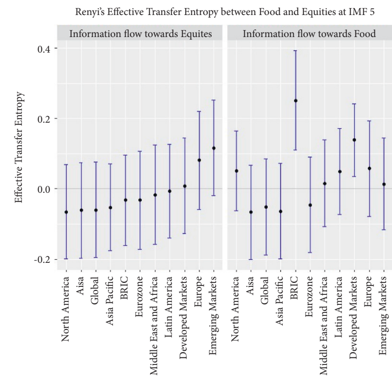
Figure 5: Continued.



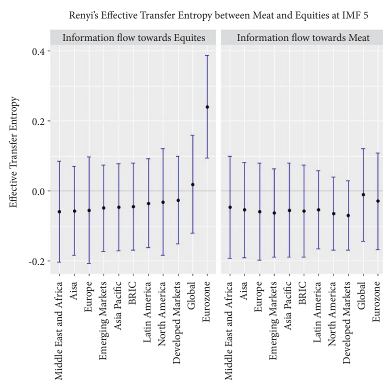
(m)



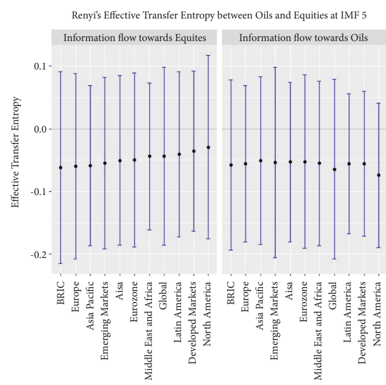
(n)



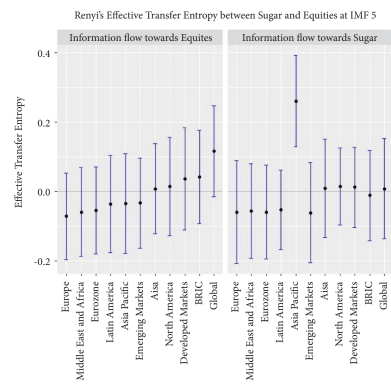
(o)



(p)

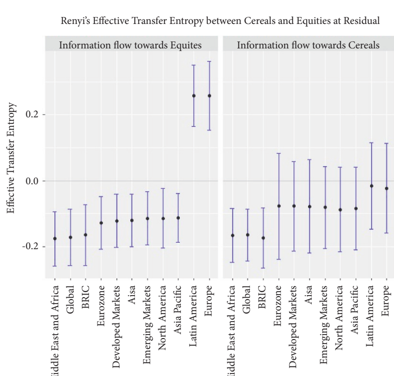


(q)

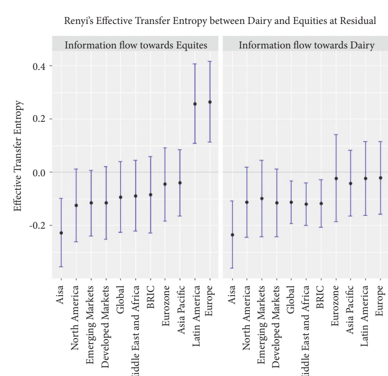


(r)

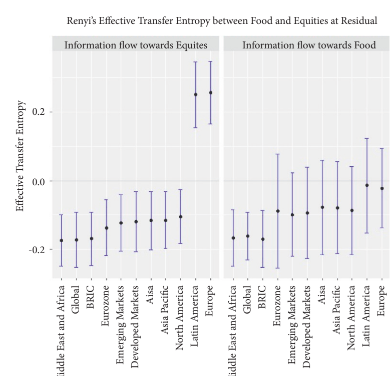
Figure 5: Transfer entropies in the mid-term. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets at medium-term scales (IMFs 3–5). (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities for IMF3 with their corresponding IMF4 and IMF5 being (g) to (l) and (m) to (r).



(a)

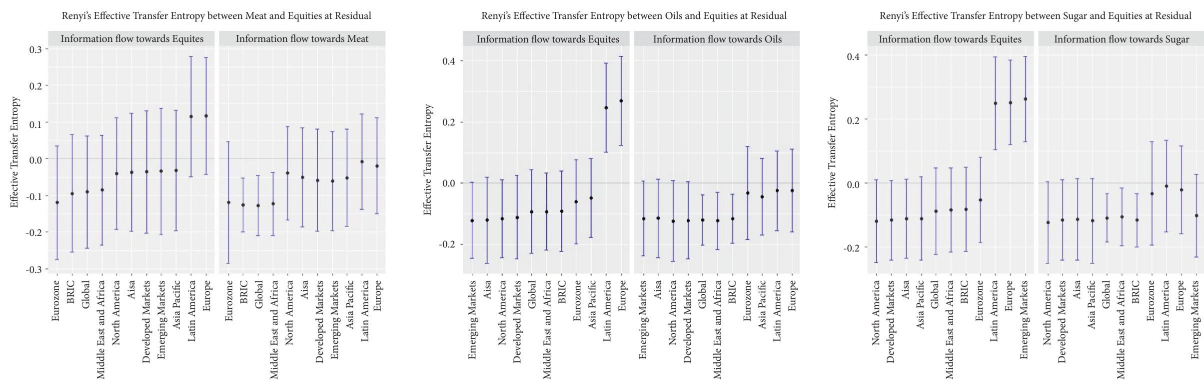


(b)



(c)

Figure 6: Continued.



(d) (e) (f)

Figure 6: Transfer entropies in the long-term. Notes: This figure presents the quantified information flow between the returns on world food commodity and regional equity markets at the long-term scale (residual IMF). (a) to (f), respectively, represent ETEs for cereals, dairy, food, meat, vegetable oil, and sugar indices against the regional equities.

diversifiers to vegetable oil. The significant positive ETE transmitters to vegetable oil include the Middle East and Africa, Eurozone, Asia-Pacific, Europe, and Asia.

Findings in the short term suggest little diversification chances. This could be attributed to the nature and degree of connectedness between agricultural commodities as espoused by Frimpong et al. [3]. In their study, they report high connectedness between agricultural commodities at high frequencies (i.e., in the short term). These findings further support the works of Živkov et al. [37] and Tiwari et al. [52] who find high linkages between agricultural commodities at short-term scales using multiscale analysis. High connectivity between commodity markets may render diversification futile, and hence, it follows the intuition that the majority of the food commodity classes fail to offer diversification benefits in the short-term frequencies.

Turning to the intermediate term (Figure 5), no diversification potential is found for cereals and dairy markets. Emerging markets, BRIC, and developed markets receive negative ETEs from food at IMF3. Global equities transmit negative flow towards food, making them diversifiable pairs. Additionally, between equities, diversifiable pairs are found for global markets against Europe, Eurozone, Middle East and Africa, and developed markets, when shocks befall equity markets. For meat, negative ETEs are transmitted to the stocks of the Middle East and Africa and developed markets, making them diversification candidates, but on the other hand, only stocks from the Middle East and Africa can diversify with meat. Between equities, when shocks befall the meat market, the Middle East and Africa and developed stocks could diversify with those from Eurozone. With more positive and fewer negative ETEs, this implies that there exist both high- and low-risk transfer entropies. Impliedly, the high-risk ETEs could be offset by their low-risk counterparts. Specifically, with the flow towards equities, the high-risk attributes of investments in equities from the Middle East and Africa and developed markets could be offset by the low-risk attributes of investments from Eurozone markets. In this case, investment in the Middle East and Africa and developed markets' equities pose less risk when the history of other equity markets is known. Stocks from Asia and the Asia-Pacific (Eurozone and Europe) are positive ETE recipients (transmitters) for vegetable oil, leaving out no diversification prospects. It is worthily noting that the varying ETE directions and significance that result in diversification potentials partly communicate the asymmetries in cross-asset connectedness [43, 57, 59, 60].

At IMF4, the Asia-Pacific and emerging markets (BRIC) receive (transmits) positive information flow from (towards) cereals. Global stocks transmit positive flow towards the dairy, meat, and vegetable oil markets. Diversification prospects are available for sugar when it experiences shocks. Sugar could diversify with Eurozone, Europe, and developed markets equities, whereas between equities, the significant diversification pairs are for Latin and North America versus Eurozone, Europe, and developed markets. In the medium term, diversification prospects keep diminishing across IMFs. When shocks are present in the cereals market, stocks from Latin and North America could diversify with cereals, whereas, between equities, the Middle East and Africa could diversify with Latin and North America. On the other hand, with shocks to equity markets, cereals could diversify with North American equities, and between equities, North America versus emerging and developed markets form the significant pairs.

Global equities could diversify with diary for all conditions, whereas, between equities, global markets versus the Middle East and Africa and Eurozone markets serve as the significant pairs when equities experience shocks. BRIC and developed markets transmit positive ETEs towards food, whereas meat transmits a positive ETE to Eurozone equities, leaving no diversification opportunity for either meat or food markets. Except for Asia-Pacific stocks that transmit a positive information flow to sugar, no significant ETEs or diversification prospects are available to the vegetable oil and sugar markets.

A significant observation in the medium term is that the diversification potentials of all commodities diminish with increasing frequencies. The main implication of this result is that when markets observe the behaviour of each other for

Table 2: Transfer entropies between world food commodities and regional equity markets.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Cereals																					
Cereals -> Asia	−0.110	0.095	−1.158	−0.055	0.087	−0.633	0.032	0.083	0.379	−0.033	0.066	−0.504	0.035	0.088	0.397	−0.063	0.071	−0.876	−0.121[b]	0.048	−2.502
Asia -> cereals	0.068	0.096	0.708	0.081	0.093	0.873	0.006	0.081	0.069	−0.021	0.090	−0.238	−0.020	0.084	−0.234	−0.034	0.076	−0.451	−0.078	0.086	−0.912
Cereals -> Asia.Pfc	−0.123	0.088	−1.394	0.067	0.084	0.796	−0.016	0.084	−0.190	−0.038	0.063	−0.605	0.268	0.089	3.005	−0.052	0.065	−0.801	−0.113[b]	0.045	−2.489
Asia.Pfc -> cereals	0.074	0.086	0.858	0.077	0.098	0.788	0.000	0.071	0.007	−0.027	0.095	−0.278	−0.027	0.082	−0.323	−0.029	0.079	−0.360	−0.084	0.076	−1.106
Cereals -> BRIC	−0.015	0.098	−0.153	0.014	0.090	0.151	−0.007	0.086	−0.079	−0.031	0.063	−0.500	−0.051	0.083	−0.612	0.100	0.072	1.377	−0.165[a]	0.056	−2.944
BRIC -> cereals	−0.023	0.091	−0.254	0.046	0.097	0.477	−0.101	0.077	−1.315	−0.038	0.085	−0.449	0.122[c]	0.073	1.675	0.028	0.086	0.324	−0.174[a]	0.055	−3.150
Cereals -> Dev.Mkt	−0.100	0.088	−1.137	0.022	0.095	0.235	0.012	0.068	0.179	−0.036	0.074	−0.492	0.122	0.084	1.456	0.045	0.060	0.756	−0.122[b]	0.049	−2.479
Dev.Mkt -> cereals	−0.096	0.090	−1.067	0.033	0.094	0.347	−0.112	0.073	−1.541	−0.035	0.068	−0.519	0.002	0.084	0.024	0.200[a]	0.073	2.748	−0.078	0.083	−0.940
Cereals -> Emg	−0.050	0.092	−0.543	0.066	0.088	0.750	0.000	0.077	0.003	−0.025	0.067	−0.381	0.274	0.080	3.438	−0.030	0.074	−0.411	−0.114[b]	0.049	−2.328
Emg -> cereals	−0.018	0.093	−0.191	0.086	0.100	0.860	−0.100	0.071	−1.413	−0.026	0.085	−0.309	−0.036	0.073	−0.489	0.156[b]	0.075	2.080	−0.081	0.076	−1.071
Cereals -> Eur	−0.047	0.084	−0.567	0.087	0.099	0.879	−0.114	0.073	−1.549	−0.028	0.072	−0.394	−0.032	0.081	−0.398	−0.071	0.070	−1.012	0.257	0.063	4.055
Eur -> cereals	0.121	0.082	1.482	0.077	0.084	0.921	−0.123[c]	0.075	−1.647	−0.030	0.072	−0.417	−0.053	0.068	−0.779	−0.061	0.087	−0.701	−0.023	0.083	−0.278
Cereals -> EurZ	−0.061	0.094	−0.649	0.084	0.103	0.820	−0.115	0.078	−1.485	−0.042	0.068	−0.620	−0.053	0.082	−0.650	−0.069	0.065	−1.066	−0.129[a]	0.048	−2.655
EurZ -> cereals	0.018	0.087	0.213	0.115	0.092	1.251	−0.109	0.072	−1.513	−0.040	0.070	−0.575	−0.046	0.062	−0.742	−0.045	0.072	−0.628	−0.078	0.097	−0.798
Cereals -> global market	0.112	0.093	1.209	0.209[b]	0.091	2.294	0.056	0.072	0.774	0.026	0.077	0.335	−0.042	0.091	−0.465	−0.063	0.055	−1.139	−0.172[a]	0.052	−3.313
Global market -> cereals	0.023	0.094	0.241	0.235	0.109	2.160	−0.018	0.070	−0.261	−0.030	0.064	−0.474	−0.051	0.083	−0.616	−0.033	0.082	−0.402	−0.165[a]	0.048	−3.445
Cereals -> Lat.Am	−0.027	0.087	−0.309	0.079	0.089	0.886	−0.035	0.075	−0.474	−0.023	0.073	−0.308	−0.039	0.081	−0.486	−0.195[a]	0.063	−3.111	0.256[a]	0.057	4.535
Lat.Am -> cereals	−0.041	0.082	−0.500	0.097	0.091	1.058	−0.107	0.081	−1.324	−0.038	0.072	−0.527	−0.059	0.072	−0.821	0.052	0.061	0.856	−0.016	0.079	−0.200
Cereals -> MEA	−0.032	0.097	−0.326	0.002	0.084	0.029	0.010	0.073	0.137	−0.016	0.063	−0.258	−0.047	0.086	−0.544	0.255[a]	0.073	3.505	−0.176[a]	0.050	−3.512

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
MEA -> cereals	0.048	0.103	0.466	0.049	0.084	0.584	−0.102	0.075	−1.367	−0.045	0.071	−0.636	−0.052	0.086	−0.607	−0.018	0.081	−0.218	−0.166[a]	0.049	−3.358
Cereals -> North.Am	−0.095	0.086	−1.099	0.039	0.087	0.446	−0.004	0.081	−0.054	−0.047	0.071	−0.664	−0.043	0.088	−0.484	−0.137[c]	0.072	−1.902	−0.114[b]	0.055	−2.092
North.Am -> cereals	−0.188[b]	0.091	−2.066	0.074	0.093	0.801	−0.091	0.081	−1.118	−0.037	0.079	−0.465	−0.051	0.087	−0.589	−0.141[a]	0.067	−2.104	−0.088	0.078	−1.123
Dairy																					
Dairy -> Asia	−0.029	0.094	−0.306	0.030	0.115	0.264	0.069	0.092	0.752	−0.032	0.066	−0.487	−0.050	0.081	−0.625	−0.054	0.079	−0.680	−0.227[a]	0.078	−2.916
Asia -> dairy	0.152[c]	0.091	1.659	0.268[a]	0.080	3.344	0.002	0.092	0.016	−0.020	0.092	−0.222	−0.040	0.083	−0.479	−0.043	0.082	−0.524	−0.234[a]	0.076	−3.058
Dairy -> Asia.Pfc	−0.046	0.095	−0.485	−0.130	0.114	−1.146	0.076	0.090	0.847	−0.037	0.067	−0.563	−0.087	0.081	−1.074	−0.061	0.086	−0.714	−0.039	0.076	−0.508
Asia.Pfc -> dairy	0.143	0.096	1.478	0.108	0.080	1.337	−0.021	0.092	−0.230	−0.031	0.090	−0.345	0.021	0.079	0.263	−0.055	0.083	−0.660	−0.041	0.075	−0.547
Dairy -> BRIC	−0.011	0.108	−0.099	−0.126	0.115	−1.089	0.008	0.088	0.096	−0.035	0.067	−0.528	−0.038	0.077	−0.491	−0.067	0.085	−0.790	−0.084	0.087	−0.963
BRIC -> dairy	0.066	0.089	0.738	0.097	0.078	1.253	−0.101	0.091	−1.113	−0.029	0.087	−0.332	−0.038	0.070	−0.543	−0.048	0.077	−0.623	−0.117[b]	0.055	−2.149
Dairy -> Dev.Mkt	0.057	0.093	0.613	−0.108	0.117	−0.920	0.071	0.085	0.835	−0.034	0.072	−0.477	0.070	0.082	0.848	−0.041	0.089	−0.467	−0.114	0.083	−1.372
Dev.Mkt -> dairy	0.181[c]	0.095	1.905	0.119	0.079	1.503	0.083	0.086	0.962	−0.032	0.072	−0.442	0.051	0.080	0.641	−0.059	0.076	−0.776	−0.115	0.077	−1.483
Dairy -> Emg	−0.009	0.099	−0.095	−0.106	0.109	−0.968	0.005	0.087	0.054	−0.038	0.073	−0.519	−0.034	0.082	−0.411	−0.049	0.086	−0.564	−0.115	0.075	−1.531
Emg -> dairy	0.045	0.097	0.462	0.104	0.081	1.284	−0.083	0.095	−0.869	−0.050	0.091	−0.548	−0.056	0.074	−0.760	−0.038	0.080	−0.479	−0.098	0.088	−1.123
Dairy -> Eur	−0.048	0.103	−0.464	−0.118	0.119	−0.991	0.052	0.093	0.559	−0.037	0.077	−0.489	−0.043	0.090	−0.477	−0.064	0.083	−0.771	0.265[a]	0.092	2.887
Eur -> dairy	−0.001	0.087	−0.011	0.103	0.070	1.463	0.063	0.085	0.743	−0.031	0.069	−0.445	−0.049	0.078	−0.626	−0.040	0.086	−0.467	−0.021	0.083	−0.259
Dairy -> EurZ	−0.015	0.107	−0.143	−0.110	0.104	−1.057	0.065	0.091	0.720	−0.029	0.061	−0.478	−0.025	0.082	−0.300	0.031	0.079	0.394	−0.045	0.084	−0.534
EurZ -> dairy	0.148	0.090	1.642	0.101	0.071	1.427	0.068	0.095	0.713	−0.040	0.078	−0.519	−0.057	0.068	−0.845	0.309[a]	0.085	3.635	−0.023	0.099	−0.227
Dairy -> global market	0.060	0.095	0.634	0.046	0.115	0.399	0.053	0.075	0.708	0.073	0.079	0.920	−0.071	0.083	−0.857	−0.146[c]	0.085	−1.710	−0.093	0.081	−1.146
Global market -> dairy	−0.060	0.086	−0.692	0.142	0.093	1.527	−0.016	0.080	−0.202	−0.075	0.069	−1.085	0.301[a]	0.083	3.638[a]	−0.144[c]	0.077	−1.872	−0.112[b]	0.049	−2.301
Dairy -> Lat.Am	−0.016	0.099	−0.162	−0.088	0.112	−0.788	−0.010	0.079	−0.126	−0.042	0.068	−0.613	−0.035	0.085	−0.414	−0.042	0.081	−0.512	0.258[a]	0.091	2.847

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Lat.Am -> dairy	0.038	0.094	0.408	−0.065	0.079	−0.828	0.027	0.090	0.301	−0.047	0.078	−0.599	−0.038	0.065	−0.591	−0.051	0.065	−0.792	−0.023	0.084	−0.271
Dairy -> MEA	−0.106	0.095	−1.120	0.012	0.109	0.109	0.007	0.084	0.084	−0.032	0.071	−0.446	0.018	0.076	0.238	−0.035	0.080	−0.441	−0.088	0.081	−1.075
MEA -> dairy	−0.007	0.096	−0.077	−0.053	0.078	−0.683	0.028	0.084	0.332	−0.027	0.078	−0.341	0.004	0.088	0.050	0.258[a]	0.077	3.332	−0.120[a]	0.049	−2.464
Dairy -> North.Am	0.048	0.096	0.503	−0.117	0.112	−1.039	−0.037	0.090	−0.413	−0.028	0.072	−0.394	−0.060	0.079	−0.763	−0.032	0.079	−0.407	−0.124	0.083	−1.485
North.Am -> dairy	0.160[c]	0.087	1.834	0.102	0.090	1.128	−0.043	0.096	−0.451	−0.026	0.077	−0.341	−0.047	0.089	−0.529	−0.062	0.064	−0.963	−0.112	0.080	−1.404
Food																					
Food -> Asia	0.103	0.089	1.162	−0.052	0.085	−0.612	0.042	0.086	0.488	−0.004	0.072	−0.061	0.011	0.084	0.126	−0.061	0.083	−0.733	−0.116[b]	0.052	−2.245
Asia -> food	0.132	0.095	1.381	−0.021	0.094	−0.217	0.157[c]	0.082	1.899	−0.074	0.080	−0.923	0.123	0.081	1.518	−0.067	0.082	−0.813	−0.078	0.084	−0.929
Food -> Asia.Pfc	0.117	0.098	1.188	0.048	0.094	0.511	0.032	0.086	0.372	−0.009	0.071	−0.133	0.083	0.083	1.012	−0.052	0.075	−0.698	−0.115[b]	0.050	−2.278
Asia.Pfc -> food	0.125	0.109	1.150	0.058	0.091	0.632	0.148[c]	0.082	1.819	−0.066	0.081	−0.808	0.051	0.079	0.647	−0.063	0.083	−0.767	−0.078	0.082	−0.961
Food -> BRIC	−0.009	0.086	−0.105	0.072	0.088	0.818	−0.046	0.084	−0.550	0.155[b]	0.075	2.077	−0.023	0.081	−0.278	−0.032	0.078	−0.417	−0.169[a]	0.047	−3.588
BRIC -> food	0.091	0.097	0.940	0.071	0.089	0.801	0.235[a]	0.079	2.984	−0.018	0.078	−0.230	−0.049	0.073	−0.675	0.252	0.086	2.938[a]	−0.170[a]	0.050	−3.390
Food -> Dev.Mkt	0.133	0.096	1.379	0.041	0.092	0.449	−0.192	0.080	−2.409	0.163[b]	0.073	2.235	−0.003	0.083	−0.036	0.009	0.082	0.108	−0.120[b]	0.053	−2.248
Dev.Mkt -> food	0.129	0.093	1.385	0.072	0.090	0.801	0.084	0.071	1.181	0.248[a]	0.075	3.314	0.063	0.078	0.797	0.139	0.062	2.218[b]	−0.094	0.081	−1.158
Food -> Emg	0.037	0.089	0.418	0.066	0.095	0.692	−0.139[c]	0.077	−1.817	0.151[b]	0.068	2.225	0.031	0.087	0.362	0.116	0.083	1.405	−0.123[b]	0.049	−2.487
Emg -> food	0.053	0.105	0.506	0.078	0.079	0.986	0.229[a]	0.080	2.872	−0.019	0.084	−0.228	0.004	0.069	0.060	0.014	0.079	0.176	−0.099	0.074	−1.334
Food -> Eur	0.130	0.101	1.284	0.066	0.091	0.723	−0.179[b]	0.082	−2.175	0.016	0.076	0.217	−0.041	0.085	−0.479	0.082	0.085	0.961	0.256[a]	0.055	4.657
Eur -> food	0.119	0.096	1.240	0.063	0.085	0.744	0.183[b]	0.075	2.424	0.238[a]	0.061	3.877	−0.062	0.065	−0.965	0.058	0.083	0.697	−0.022	0.071	−0.311
Food -> EurZ	0.115	0.097	1.185	0.074	0.097	0.768	−0.142[c]	0.074	−1.911	0.027	0.056	0.480	−0.033	0.080	−0.414	−0.032	0.085	−0.378	−0.137[a]	0.049	−2.796
EurZ -> food	0.107	0.094	1.131	0.050	0.085	0.590	0.229[a]	0.082	2.798	0.218	0.063	3.441	−0.043	0.077	−0.562	−0.045	0.083	−0.549	−0.088	0.101	−0.871
Food -> global market	0.001	0.082	0.007	0.038	0.087	0.444	0.000	0.064	0.007	0.000	0.079	0.001	0.006	0.083	0.072	−0.060	0.083	−0.718	−0.173[a]	0.049	−3.525

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Global market -> food	0.026	0.101	0.255	−0.025	0.092	−0.270	0.013	0.075	0.171	−0.132[b]	0.066	−1.994	0.010	0.083	0.125	−0.052	0.083	−0.622	−0.161[a]	0.043	−3.789
Food -> Lat.Am	0.212[b]	0.090	2.361	0.016	0.091	0.173	−0.133[c]	0.073	−1.827	0.082	0.059	1.391	−0.034	0.086	−0.396	−0.006	0.081	−0.077	0.251[a]	0.058	4.304
Lat.Am -> food	−0.001	0.104	−0.012	0.013	0.097	0.131	0.060	0.090	0.667	0.078	0.065	1.195	−0.062	0.072	−0.869	0.050	0.075	0.670	−0.015	0.083	−0.175
Food -> MEA	0.103	0.090	1.150	0.053	0.086	0.619	−0.139[c]	0.075	−1.870	0.065	0.071	0.920	−0.039	0.077	−0.502	−0.017	0.086	−0.194	−0.175[a]	0.045	−3.857
MEA -> food	0.028	0.096	0.287	0.167[c]	0.093	1.789	0.144	0.072	2.001	0.258[c]	0.071	3.612	−0.049	0.077	−0.639	0.016	0.075	0.208	−0.166[a]	0.050	−3.336
Food -> North.Am	0.140	0.092	1.526	0.050	0.089	0.564	−0.119	0.088	−1.349	0.044	0.072	0.613	−0.053	0.082	−0.643	−0.065	0.082	−0.802	−0.105[b]	0.048	−2.177
North.Am -> food	0.134	0.091	1.472	0.096	0.104	0.931	−0.032	0.086	−0.369	−0.081	0.067	−1.208	−0.057	0.078	−0.732	0.051	0.069	0.745	−0.087	0.078	−1.113
Meat																					
Meat -> Asia	0.065	0.084	0.774	−0.020	0.091	−0.224	−0.035	0.082	−0.434	0.069	0.071	0.974	−0.054	0.083	−0.656	−0.056	0.077	−0.729	−0.037	0.098	−0.384
Asia -> meat	0.096	0.090	1.074	0.164[c]	0.086	1.896	−0.119	0.080	−1.493	0.074	0.082	0.901	−0.061	0.084	−0.735	−0.054	0.083	−0.656	−0.051	0.082	−0.616
Meat -> Asia.Pfc	0.061	0.087	0.705	−0.010	0.098	−0.101	−0.139[c]	0.080	−1.730	0.057	0.075	0.750	−0.042	0.086	−0.490	−0.046	0.075	−0.604	−0.032	0.100	−0.324
Asia.Pfc -> meat	0.095	0.107	0.890	0.189[c]	0.097	1.941	−0.034	0.072	−0.472	0.079	0.088	0.903	−0.056	0.084	−0.661	−0.054	0.081	−0.669	−0.052	0.081	−0.645
Meat -> BRIC	−0.066	0.090	−0.727	−0.082	0.100	−0.819	−0.037	0.082	−0.457	0.032	0.067	0.477	−0.030	0.085	−0.354	−0.044	0.076	−0.584	−0.095	0.097	−0.978
BRIC -> meat	0.033	0.099	0.335	0.216[b]	0.090	2.418	−0.029	0.070	−0.417	0.034	0.090	0.380	−0.058	0.076	−0.765	−0.056	0.080	−0.705	−0.126[a]	0.045	−2.815
Meat -> Dev.Mkt	0.074	0.085	0.864	0.024	0.093	0.262	0.027	0.072	0.373	−0.131[c]	0.072	−1.809	0.020	0.095	0.208	−0.025	0.076	−0.335	−0.036	0.101	−0.356
Dev.Mkt -> meat	0.096	0.083	1.157	0.109	0.095	1.147	−0.006	0.065	−0.088	−0.122	0.076	−1.604	0.003	0.088	0.036	−0.070	0.060	−1.152	−0.059	0.085	−0.695
Meat -> Emg	0.020	0.091	0.219	−0.146	0.098	−1.482	−0.019	0.073	−0.267	0.036	0.065	0.549	−0.034	0.083	−0.404	−0.049	0.075	−0.649	−0.034	0.104	−0.331
Emg -> meat	0.027	0.092	0.297	0.093	0.093	1.001	−0.031	0.081	−0.383	0.032	0.093	0.348	−0.065	0.066	−0.994	−0.062	0.077	−0.810	−0.061	0.082	−0.748
Meat -> Eur	0.041	0.098	0.417	0.003	0.095	0.032	0.020	0.076	0.265	0.041	0.072	0.565	−0.039	0.066	−0.587	−0.055	0.092	−0.591	0.116	0.097	1.201
Eur -> meat	0.028	0.099	0.287	0.186[b]	0.089	2.093	−0.007	0.071	−0.092	−0.065	0.066	−0.978	−0.064	0.064	−1.007	−0.058	0.085	−0.692	−0.019	0.079	−0.241
Meat -> EurZ	−0.018	0.092	−0.196	−0.006	0.101	−0.056	0.018	0.078	0.235	0.132[c]	0.069	1.905	−0.024	0.070	−0.339	0.241	0.089	2.711	−0.120	0.094	−1.275
EurZ -> meat	0.088	0.096	0.913	0.168[b]	0.083	2.025	−0.017	0.067	−0.252	−0.047	0.073	−0.640	−0.063	0.064	−0.988	−0.029	0.084	−0.339	−0.119	0.101	−1.185

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Meat -> global market	0.027	0.077	0.349	−0.109	0.103	−1.058	0.085	0.066	1.292	−0.094	0.085	−1.116	−0.027	0.083	−0.325	0.019	0.085	0.228	−0.091	0.093	−0.975
Global market -> meat	−0.043	0.095	−0.449	−0.096	0.098	−0.973	−0.018	0.075	−0.246	−0.030	0.065	−0.460	0.256[a]	0.075	3.438	−0.011	0.081	−0.133	−0.127[b]	0.050	−2.543
Meat -> Lat.Am	0.017	0.088	0.191	−0.094	0.095	−0.990	−0.020	0.077	−0.255	0.019	0.065	0.289	−0.032	0.081	−0.394	−0.034	0.078	−0.443	0.114	0.100	1.145
Lat.Am -> meat	0.037	0.092	0.400	0.179[b]	0.086	2.066	−0.008	0.072	−0.108	−0.046	0.069	−0.666	−0.068	0.066	−1.033	−0.053	0.068	−0.786	−0.008	0.079	−0.102
Meat -> MEA	0.032	0.088	0.366	−0.104	0.088	−1.187	0.019	0.066	0.289	−0.133[b]	0.067	−1.994	−0.051	0.081	−0.629	−0.058	0.088	−0.662	−0.085	0.091	−0.942
MEA -> meat	−0.070	0.090	−0.779	0.021	0.089	0.235	−0.023	0.070	−0.329	−0.131[c]	0.078	−1.674	−0.053	0.081	−0.651	−0.046	0.089	−0.521	−0.123[b]	0.052	−2.342
Meat -> North.Am	−0.043	0.087	−0.491	0.001	0.094	0.008	−0.002	0.083	−0.020	0.017	0.062	0.279	−0.052	0.077	−0.675	−0.031	0.093	−0.336	−0.040	0.093	−0.434
North.Am -> meat	0.103	0.093	1.104	0.024	0.100	0.241	−0.010	0.073	−0.138	−0.083	0.068	−1.228	−0.056	0.071	−0.798	−0.064	0.064	−1.005	−0.039	0.078	−0.509
Veg. oil																					
Veg. oil -> Asia	0.015	0.099	0.150	−0.102	0.084	−1.212	0.041	0.084	0.487	0.154[b]	0.065	2.355	−0.054	0.083	−0.654	−0.050	0.082	−0.611	−0.120	0.086	−1.408
Asia -> veg. oil	0.034	0.095	0.365	0.004	0.086	0.046	0.149[c]	0.077	1.940	−0.010	0.090	−0.113	−0.050	0.079	−0.627	−0.053	0.077	−0.687	−0.114	0.078	−1.475
Veg. oil -> Asia.Pfc	0.013	0.086	0.145	−0.110	0.086	−1.275	−0.054	0.089	−0.603	0.158[a]	0.061	2.606	−0.049	0.085	−0.581	−0.059	0.078	−0.755	−0.048	0.079	−0.611
Asia.Pfc -> veg. oil	0.015	0.099	0.155	0.004	0.089	0.040	0.144[c]	0.082	1.756	−0.015	0.086	−0.181	−0.053	0.089	−0.599	−0.051	0.082	−0.621	−0.044	0.076	−0.575
Veg. oil -> BRIC	−0.093	0.098	−0.955	0.012	0.091	0.127	−0.027	0.083	−0.323	0.040	0.063	0.638	−0.033	0.089	−0.376	−0.062	0.093	−0.662	−0.090	0.079	−1.138
BRIC -> veg. oil	−0.035	0.096	−0.363	0.201[b]	0.086	2.332	0.074	0.081	0.910	0.008	0.081	0.104	−0.054	0.072	−0.761	−0.058	0.083	−0.699	−0.116[b]	0.048	−2.402
Veg. oil -> Dev.Mkt	0.125	0.091	1.367	−0.063	0.091	−0.695	−0.131[c]	0.074	−1.775	0.061	0.064	0.959	0.018	0.086	0.207	−0.036	0.078	−0.460	−0.111	0.083	−1.335
Dev.Mkt -> veg. oil	0.035	0.092	0.382	−0.033	0.088	−0.373	0.059	0.082	0.723	0.008	0.069	0.110	0.018	0.091	0.202	−0.055	0.070	−0.787	−0.121	0.077	−1.574
Veg. oil -> Emg	−0.021	0.096	−0.222	0.028	0.096	0.296	−0.200[b]	0.079	−2.529	0.037	0.071	0.522	−0.047	0.083	−0.567	−0.055	0.083	−0.656	−0.121	0.075	−1.613
Emg -> veg. oil	0.032	0.100	0.322	0.208[b]	0.092	2.259	0.063	0.076	0.824	0.012	0.081	0.152	−0.056	0.072	−0.776	−0.053	0.092	−0.575	−0.115	0.074	−1.558
Veg. oil -> Eur	0.106	0.099	1.069	−0.077	0.087	−0.886	−0.038	0.080	−0.475	0.003	0.065	0.053	−0.046	0.073	−0.637	−0.060	0.090	−0.661	0.269[a]	0.088	3.053

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Eur -> veg. oil	0.013	0.087	0.154	0.005	0.086	0.053	0.147[c]	0.080	1.839	0.463[a]	0.073	6.325	−0.058	0.068	−0.849	−0.056	0.076	−0.738	−0.023	0.082	−0.282
Veg. oil -> EurZ	0.028	0.094	0.304	−0.070	0.092	−0.767	−0.056	0.081	−0.685	−0.041	0.074	−0.552	−0.024	0.087	−0.271	−0.050	0.085	−0.591	−0.061	0.083	−0.730
EurZ -> veg. oil	0.109	0.094	1.157	−0.007	0.081	−0.085	0.264[a]	0.079	3.348	0.223[a]	0.065	3.437	−0.046	0.067	−0.694	−0.052	0.084	−0.623	−0.032	0.092	−0.351
Veg. oil -> global market	0.102	0.090	1.133	0.045	0.091	0.500	0.062	0.072	0.862	0.064	0.081	0.786	−0.023	0.090	−0.252	−0.044	0.086	−0.508	−0.092	0.083	−1.120
Global market -> veg. oil	0.037	0.081	0.458	−0.049	0.097	−0.507	−0.033	0.076	−0.432	0.025	0.061	0.403	0.259[a]	0.082	3.163	−0.064	0.087	−0.739	−0.119[b]	0.050	−2.398
Veg. oil -> Lat.Am	0.040	0.091	0.440	0.066	0.091	0.725	−0.189	0.073	−2.592	−0.032	0.066	−0.480	−0.034	0.083	−0.407	−0.040	0.080	−0.504	0.246[a]	0.088	2.796
Lat.Am -> veg. oil	0.106	0.093	1.145	0.033	0.089	0.369	−0.007	0.086	−0.084	0.011	0.068	0.164	−0.052	0.075	−0.703	−0.056	0.068	−0.816	−0.024	0.079	−0.307
Veg. oil -> MEA	0.035	0.094	0.377	−0.035	0.080	−0.436	−0.196[a]	0.076	−2.590	0.057	0.072	0.788	−0.052	0.088	−0.590	−0.044	0.071	−0.616	−0.092	0.077	−1.203
MEA -> veg. oil	0.098	0.098	1.004	0.175[c]	0.090	1.932	0.154	0.075	2.049	0.010	0.075	0.128	−0.062	0.084	−0.732	−0.055	0.080	−0.686	−0.123[b]	0.056	−2.175
Veg. oil -> North.Am	0.114	0.092	1.241	−0.041	0.085	−0.479	−0.076	0.084	−0.911	0.032	0.074	0.433	−0.041	0.077	−0.535	−0.029	0.089	−0.328	−0.116	0.077	−1.499
North.Am -> veg. oil	0.122	0.091	1.339	−0.043	0.091	−0.470	−0.061	0.088	−0.687	−0.060	0.063	−0.957	−0.056	0.077	−0.730	−0.074	0.070	−1.059	−0.123	0.080	−1.541
Sugar																					
Sugar -> Asia	0.136	0.098	1.395	−0.145	0.093	−1.566	0.034	0.091	0.367	−0.043	0.065	−0.669	−0.048	0.054	−0.881	0.008	0.079	0.102	−0.112	0.075	−1.486
Asia -> sugar	0.079	0.095	0.829	−0.124	0.082	−1.522	0.138	0.084	1.642	−0.026	0.080	−0.325	−0.019	0.088	−0.215	0.010	0.086	0.111	−0.114	0.078	−1.466
Sugar -> Asia.Pfc	0.156[c]	0.093	1.677	−0.199[a]	0.098	−2.022	0.052	0.084	0.619	−0.041	0.066	−0.624	−0.069	0.065	−1.064	−0.035	0.087	−0.397	−0.111	0.080	−1.394
Asia.Pfc -> sugar	0.056	0.092	0.605	−0.043	0.086	−0.502	0.146[c]	0.079	1.860	−0.052	0.093	−0.554	−0.015	0.092	−0.163	0.260[a]	0.080	3.259	−0.119	0.080	−1.476
Sugar -> BRIC	0.161	0.105	1.539	−0.081	0.101	−0.801	−0.045	0.081	−0.557	−0.034	0.074	−0.464	−0.059	0.072	−0.818	0.042	0.082	0.517	−0.082	0.080	−1.025
BRIC -> sugar	0.159[c]	0.084	1.885	0.085	0.089	0.956	0.066	0.086	0.766	−0.033	0.080	−0.415	0.042	0.075	0.559	−0.011	0.079	−0.145	−0.117[b]	0.051	−2.285
Sugar -> Dev.Mkt	0.156[c]	0.088	1.772	−0.064	0.100	−0.639	−0.142[c]	0.079	−1.790	−0.025	0.069	−0.364	−0.099[c]	0.058	−1.695	0.037	0.090	0.412	−0.116	0.076	−1.532
Dev.Mkt -> sugar	0.160[c]	0.090	1.788	0.050	0.093	0.538	0.056	0.070	0.792	−0.043	0.078	−0.556	−0.034	0.088	−0.389	0.013	0.070	0.178	−0.116	0.076	−1.525
Sugar -> Emg	0.066	0.096	0.693	−0.076	0.099	−0.771	−0.207[b]	0.083	−2.507	−0.043	0.070	−0.618	0.005	0.062	0.081	−0.033	0.079	−0.415	0.263[a]	0.081	3.260

Table 2: Continued.

	Composite			IMF1			IMF2			IMF3			IMF4			IMF5			Residual		
	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat	ETE	SE	T-stat
Emg -> sugar	0.074	0.094	0.784	0.075	0.091	0.824	0.058	0.081	0.720	−0.037	0.085	−0.438	−0.034	0.074	−0.463	−0.061	0.088	−0.692	−0.102	0.078	−1.307
Sugar -> Eur	0.095	0.098	0.969	−0.120	0.101	−1.194	−0.048	0.076	−0.629	−0.046	0.072	−0.637	−0.138	0.060	−2.314	−0.071	0.076	−0.944	0.251^{a}	0.081	3.118
Eur -> sugar	−0.014	0.094	−0.146	−0.045	0.080	−0.567	0.148^{c}	0.077	1.924	−0.029	0.073	−0.391	−0.022	0.075	−0.300	−0.059	0.090	−0.661	−0.022	0.084	−0.264
Sugar -> EurZ	0.121	0.100	1.219	−0.127	0.088	−1.437	−0.056	0.076	−0.736	−0.052	0.072	−0.719	-0.156^{b}	0.064	−2.419	−0.054	0.076	−0.708	−0.054	0.081	−0.663
EurZ -> sugar	0.036	0.095	0.380	−0.064	0.080	−0.794	0.260^{a}	0.077	3.372	−0.035	0.068	−0.519	−0.017	0.061	−0.279	−0.059	0.082	−0.716	−0.033	0.098	−0.336
Sugar -> global market	0.150^{c}	0.086	1.741	−0.026	0.094	−0.278	−0.017	0.069	−0.249	−0.016	0.079	−0.207	−0.052	0.072	−0.723	0.117	0.079	1.474	−0.089	0.082	−1.079
Global market -> sugar	-0.193^{b}	0.091	−2.128	−0.019	0.097	−0.193	0.011	0.075	0.147	0.023	0.061	0.381	−0.123	0.089	−1.375	0.008	0.088	0.091	−0.109	0.046	−2.374
Sugar -> Lat.Am	0.112	0.095	1.174	−0.120	0.102	−1.182	-0.176^{b}	0.075	−2.364	−0.043	0.071	−0.613	0.162^{a}	0.062	2.610	−0.036	0.085	−0.427	0.249^{a}	0.089	2.808
Lat.Am -> sugar	0.028	0.087	0.319	0.144^{c}	0.083	1.727	0.009	0.087	0.106	−0.026	0.071	−0.370	0.067	0.076	0.888	−0.053	0.069	−0.759	−0.010	0.087	−0.115
Sugar -> MEA	0.213^{b}	0.092	2.318	−0.084	0.100	−0.839	-0.197^{b}	0.077	−2.552	−0.035	0.067	−0.517	0.062	0.063	0.990	−0.059	0.078	−0.758	−0.084	0.080	−1.051
MEA -> sugar	0.204^{b}	0.093	2.199	0.060	0.080	0.754	0.149^{c}	0.077	1.952	−0.018	0.069	−0.256	−0.070	0.089	−0.789	−0.056	0.083	−0.671	-0.105^{c}	0.055	−1.926
Sugar -> North.Am	0.133	0.088	1.522	0.007	0.107	0.070	−0.075	0.087	−0.868	−0.046	0.064	−0.716	0.124^{b}	0.062	1.989	0.015	0.086	0.173	−0.120	0.078	−1.532
North.Am -> sugar	0.154^{c}	0.087	1.762	0.031	0.097	0.320	−0.043	0.079	−0.542	−0.039	0.070	−0.564	−0.045	0.083	−0.535	0.015	0.067	0.216	−0.124	0.078	−1.599

Notes. Asia.Pfc: Asia-Pacific; Dev.Mkt: developed markets; Emg: emerging markets; Eur: Europe markets; EurZ: Eurozone; Lat.Am: Latin America; North.Am: North America. Significance levels are ^{a}(1%), ^{b}(5%), and ^{c}(10%). ETE – effective transfer entropy; SE – standard error; T-stats – the resultant *t*-statistics of ETEs.

quite a long period, they tend to start getting saturated with information transfer. Ideally, reassessing the performance of commodities and equities in a given portfolio is key to minimising portfolio and cross-market risks through information transfer. This emphasises the heterogeneity of cross-asset linkages, as revealed in the empirical literature on commodity and stock markets (see, e.g., [44, 45, 57–60, 78]). This is not surprising since the effect of significant or key events in the medium term is likely to arouse market linkages [9]. Thus, though some diversification prospects are found, they may last with the duration of the key events. Impliedly, vanishing diversification potentials may correspond to the emergence and passage of key events in the medium term [8, 9, 80].

We now turn to the long-term ETEs, the residual. For cereals and food, except those of Latin America and Europe (which are positive ETE recipients), all other regional equities are negative ETE recipients. Equities from the Middle East and Africa, global markets, Eurozone, developed markets, Asia and the Asia-Pacific, emerging markets, and North America are significant diversifiers for cereals and food; between equities, they are diversification candidates for stocks from Latin America and Europe. The Middle East and Africa, global markets, and BRIC markets transmit negative ETEs to cereals, making them significant diversifiers with both cereals and food. Upon shocks to the dairy market, Asian stocks are significant diversifiers, which further create diversification pairs with equities from Latin America and Europe. Amid equity market shocks, Asia, global, Middle East and Africa, and BRIC markets could diversify with dairy.

For meat, vegetable oil, and sugar, no significant diversification pairs are available when the commodity markets experience shocks. However, when equity markets are affected by shocks, equities from BRIC, global markets, and the Middle East and Africa could be diversified with any meat, vegetable oil, and sugar. In the long term, we find more significant diversification potentials between food commodity markets and regional and/or global equities. We attribute this to the fundamental properties of commodities as diversifiers for traditional assets [79]. The intuition is that as Yang et al. [80] espouse, the long-term is driven by fundamentals between markets, it is expected that regardless of the effects of investor sentiments and key events, the information flow between commodity markets and regional and global equity markets would most likely result from the fundamental dynamics that apply in all markets.

The results in the frequency domain reveal more significant ETEs relative to those of the composite, which only revealed a diversification opportunity between sugar and global equity markets. Impliedly, frequency-domain analysis unveils hidden significant ETEs at the composite level. This suggests that taking into consideration the heterogeneity of commodity markets and market players alike [3, 50, 57, 60, 79], the essence of the frequency-domain analysis cannot be downplayed.

From Table 2, we find that cereals and dairy markets could either diversify with or be diversified by global equities nearing the end of the mid term or in the long term only. Thus, should either market (cereals or dairy) experience shocks, regional and global equities may provide diversification benefits. Similarly, in times of shocks to regional and global equities, cereals and dairy could offer a safety net for international investors. However, these could manifest in the long term only.

Moreover, we report that food and meat markets stand the chance to offer diversification opportunities in the latter part of the short and long terms only. In the short term, diversification opportunities for portfolios containing food and meat are likely to achieve mixed combinations between commodities and stocks as well as between equities alone. Similar opportunities avail in the long term, but for the meat market, such opportunities are largely between meat and equity markets since the chances for all equity diversification are very slim. The results for the meat market are more likened to that of the vegetable oil market, which also reveals diversification prospects between oil and regional and global equity markets in the short- and long-term periods only. The stand out agricultural commodity market from the FAO indices is that of sugar. We report that sugar provides diversification opportunities with regional and global equity markets generally across all time horizons. Thus, there is a high tendency to use global equities to hedge against losses from the sugar market in times of crisis, and sugar could also hedge against the losses from global equities amid crises periods. Table 3 summarises the diversification prospects between world food commodities and regional equities resulting from information flow.

5.3. Economic Implications of the Results. Per the competitive markets hypothesis, information flow between markets intensify due to the behaviour of market participants [9]. Since the behaviour of these market participants evolves, our results are essential to investors who trade along timelines corresponding to the short-, medium-, and long-term horizons. Notably, at the composite level, where no assumption is made about the complexity and nonlinearity of the data series, we identify that investors could only resort to investments in global stocks and sugar for diversification when the traditional stock market experiences any shock. Aside from sugar and global equities, all other food commodities and equity markets have no significant diversification potential at the composite level. The assumption at the composite level is that market participants respond equally to market dynamics. This assumption is inconsistent with Mongars and Marchal-Dombrat's [81] observation that investor response to commodity market dynamics is heterogeneous, and this is consistent with the conclusions made by recent works [3, 41, 43, 57, 60, 61, 78, 79]. The frequency-domain analysis overcomes this limitation.

Speculators and hedgers are interested in short-term gains, whereas the interest of institutional investors lies in long-term returns. In between short- and long-term investors are medium-term investors, who regularly monitor and rebalance their portfolios to take advantage of medium-term gains. Our results in the frequency domain make a relevant contribution as key inputs for investment decisions based on time scales. Specifically, in the short term, our

Table 3: Summary of results.

Series	Commodity	Diversification potentials: Shocks to commodity markets: Commodity vs. equities	Shocks to commodity markets: Between equities	Shocks to equity markets: Commodity vs. equities	Shocks to equity markets: Between equities
Composite	Cereals	✗	✗	North America vs. cereals	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	✗	✗	Global markets vs. sugar	Global markets vs. North America, developed markets, BRIC, and MEA
IMF1, short term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	Sugar vs. Asia-Pacific	✗	✗	✗
IMF2, short term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	Food vs. developed markets, European, Eurozone, MEA, emerging markets, and Latin America	✗	✗	✗
	Meat	Meat vs. Asia-Pacific	✗	✗	✗
	Veg. oil	Veg. oil vs. emerging, MEA, Latin America, and developed markets	✗	✗	✗
	Sugar	Sugar vs. emerging markets, MEA, Latin America, and developed markets	✗	✗	✗
IMF3, mid term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	Food vs. global market	Global vs. global vs. Europe, Eurozone, MEA, and developed markets)
	Meat	Meat vs. MEA and developed markets	MEA and developed markets vs. Eurozone	Meat vs. MEA	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	✗	✗	✗	✗
IMF4, mid term	Cereals	✗	✗	✗	✗
	Dairy	✗	✗	✗	✗
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	Sugar vs. developed, Eurozone, and Europe	Developed, Eurozone, and Europe vs. North America and Latin America	✗	✗

Table 3: Continued.

Series	Commodity	Diversification potentials: Shocks to commodity markets — Commodity vs. equities	Shocks to commodity markets — Between equities	Shocks to equity markets — Commodity vs. equities	Shocks to equity markets — Between equities
IMF5, mid term	Cereals	Cereals vs. North America and Latin America	North American and Latin America vs. MEA	Cereals vs. North America	North America vs. emerging and developed markets
	Dairy	Dairy vs. global markets	✗	Dairy vs. global	Global markets vs. developed and Eurozone markets
	Food	✗	✗	✗	✗
	Meat	✗	✗	✗	✗
	Veg. oil	✗	✗	✗	✗
	Sugar	✗	✗	✗	✗
Residual, long term	Cereals	Cereals vs. MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and the Asia-Pacific	MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and Asia-Pacific vs. Latin America and Europe	Cereals vs. MEA, global markets, and BRIC	✗
	Dairy	Dairy vs. Asia	Asia vs. Latin America and Europe	Dairy vs. Asia, global markets, MEA, and BRIC	✗
	Food	Food vs. MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and the Asia Pacific	MEA, global markets, BRIC, Eurozone, developed markets, Asia, emerging markets, North America, and Asia-Pacific vs. Latin America and Europe	Food vs. MEA, global markets, and BRIC	✗
	Meat	✗	✗	Meat vs. BRIC, global markets, and MEA	✗
	Veg. oil	✗	✗	Veg. oil vs. BRIC, global markets, and MEA	✗
	Sugar	✗	✗	Sugar vs. BRIC, global markets, and MEA	✗

Note: This table presents the summarised diversification or hedging pairs between commodities and regional equities as well as between equities. MEA – the Middle East and Africa and veg. oil – vegetable oil.

findings explicate that cereals, dairy, food, meat, and vegetable oil fail to offer diversification benefits to investors. For speculators and hedgers, investment in sugar may most likely suffice their investment needs, when combined with regional equities.

For medium-term investors, food, meat, and sugar may serve as potential diversifiers for regional or global equities, but their role as diversifiers may be inconsistent owing to the inconsistent significant relationships found with equity markets. Impliedly, portfolios containing investments in food, meat, and sugar should be monitored in the medium term to make effective rebalancing assessments.

On a good note, long-term investors, such as institutional investors, stand the chance of benefiting from all commodity markets. Specifically, cereals, dairy, food, meat, vegetable oil, and sugar consistently serve as diversifiers for regional and global equity investments in the long term. From this observation, we conclude that the fundamental role of commodities as diversifiers [3, 43, 57, 63, 79, 82] is corroborated through information transfer. Thus, based on the intrinsic information shared by commodity and equity markets, the dynamics between the two asset classes revert to their fundamental linkages in the long term.

6. Conclusion

The intrinsic information shared by financial assets provides a means of assessing their mutual linkages. In times of crisis, spillovers and information flow between markets increase, and this drives empirical investigations into the degree of connectedness between financial assets. Commodity markets are seeing growing financialisation into the traditional market due to their ability to offer diversification benefits to traditional assets, and this has been termed the financialisation of commodities. In the wake of COVID-19 and other recent episodes of financial crises, the empirical literature has focused on the return and volatility connectedness between all sorts of commodity markets, with no evidence of the degree of information transfer between them. To complement the assessments on the competitive market hypothesis, we take the direction of information flow and focus on commodity markets, which have seen several volatilities in recent periods.

From this backdrop, we investigate the situated information transfers between commodity and equity markets' returns by employing the FAO food commodity and its constituents' indices and the regional stock markets. We contribute to the literature on commodity markets by providing empirical evidence on the quantitative information transfers between food commodity and equity markets' returns. Through this analysis, potential diversification benefits between commodity and/or equity markets are revealed across investment scales, which suit the investment needs of short-, medium-, and long-term investors.

Our findings are suggestive of the fact that the behaviour of equity markets could be observed by commodity markets through the mutual information they share, and this helps determine which markets are effective pairs for diversification. Mainly, our results indicate that information flow between commodity and equity markets vary across time scales or frequencies. To inform interested market participants, our composite transfer entropies suggest that out of the food commodity classes, only sugar serves as a significant diversifier. The diversification potentials of cereals, dairy, food, meat, and vegetable oil prove insignificant on the composite scale. Findings from the frequency domain, which provide insightful results for time horizon investors, reveal that cereals and dairy are diversifiers in the long term only; food and meat are significant diversifiers in the short- and long-term periods only; a consistent diversifier across the short-, medium-, and long-term horizons is sugar. These assets diversify with particular regional and/or global equity markets, which should be noted by investors.

Our results have several implications for both private sector investment management techniques and public sector monitoring and policy design. The portfolio concentration risk of private sector investors is directly related to connectedness, and hence, investors should utilise the knowledge about the degree of connection between commodity and equity markets for effective portfolio management. Portfolios should be monitored along with investment time scales, whilst taking into consideration the linkage between assets due to information flow. Furthermore, empirical evidence suggests that the connectedness between commodities intensifies during crises, and this translates to the broader macroeconomy. Hence, regulators should capitalise on the knowledge concerning the information flow between commodity and equity markets in devising and monitoring market policies in the public sector.

From the findings of this study, the quantile dependencies between the studied variables could be explored, as they were unrevealed by the employed methodologies. As a result, future studies could assess the conditional dependence between food commodity and equity markets. The family of quantile regressions may be essential in this regard. Additionally, it would be fascinating to draw inferences from econophysics methodologies such as the detrended cross-correlation analysis [83] and sliding windows detrended fluctuation technique [84], among others.

Data Availability

The food commodity indices are available at https://www.fao.org/; the data on regional stock markets indices are accessible from EquityRT website (https://equityrt.com/).

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References

[1] S. K. Agyei, Z. Isshaq, S. Frimpong, A. M. Adam, A. Bossman, and O. Asiamah, "COVID-19 and food prices in sub-Saharan Africa," *African Development Review*, vol. 1–12, 2021.

[2] I. O. Fasanya and T. F. Odudu, "Modeling return and volatility spillovers among food prices in Nigeria," *Journal of Agriculture and Food Research*, vol. 2, Article ID 100029, 2020.

[3] S. Frimpong, E. N. Gyamfi, Z. Ishaq et al., "Can Global Economic Policy Uncertainty Drive the Interdependence of Agricultural Commodity Prices? Evidence from Partial Wavelet Coherence Analysis," *Complexity*, vol. 2021, 2021.

[4] Fao, "World food situation. Food Price Index," 2021, https://www.fao.org/worldfoodsituation/foodpricesindex/en/.

[5] Fao, "World food situation. Food Price Index," 2022, https://www.fao.org/worldfoodsituation/foodpricesindex/en/.

[6] UNECA, *Commodity Markets in Africa to Remain Volatile amid COVID-19*TeleSUR World News, Caracas, Venezuela, 2021.

[7] M. A. Hernandez, R. Ibarra, and D. R. Trupkin, "How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets," *European Review of Agricultural Economics*, vol. 41, no. 2, pp. 301–325, 2014.

[8] A. Bossman, "Information flow from COVID-19 pandemic to Islamic and conventional equities: an ICEEMDAN-induced transfer entropy analysis," *Complexity*, vol. 2021, pp. 1–20, 2021.

[9] P. Owusu Junior, S. Frimpong, A. M. Adam et al., "COVID-19 as information transmitter to global equity markets: evidence from CEEMDAN-based transfer entropy approach," *Mathematical Problems in Engineering*, vol. 2021, 2021.

[10] K. Tang and W. Xiong, "Index investment and the financialization of commodities," *Financial Analysts Journal*, vol. 68, no. 6, pp. 54–74, 2012.

[11] C. Hu, Z. Li, and X. Liu, "Liquidity shocks, commodity financialization, and market comovements," *Journal of Futures Markets*, vol. 40, no. 9, pp. 1315–1336, 2020.

[12] S. Śmiech, M. Papież, K. Fijorek, and M. A. Dąbrowski, "What drives food price volatility? Evidence based on a generalized VAR approach applied to the food, financial and energy markets," *Economics*, vol. 13, pp. 1–32, 2019.

[13] B. J. Deaton and B. J. Deaton, "Food security and Canada's agricultural system challenged by COVID-19," *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, vol. 68, no. 2, pp. 143–149, 2020.

[14] D. Headey, S. Malaiyandi, and S. Fan, "Navigating the perfect storm: reflections on the food, energy, and financial crises,"

Agricultural Economics, vol. 41, no. SUPPL. 1, pp. 217–228, 2010.

[15] W. Hanif, J. Areola Hernandez, S. J. H. Shahzad, and S. M. Yoon, "Tail dependence risk and spillovers between oil and food prices," *The Quarterly Review of Economics and Finance*, vol. 80, pp. 195–209, 2021.

[16] T. Schreiber, "Measuring information transfer," *Physical Review Letters*, vol. 85, no. 2, pp. 461–464, 2000.

[17] F. I. Dretske, "Knowledge and the flow of information," in *Dialogue*MIT Press, Cambridge, MA, 1981.

[18] J. Pearl, "Causal inference in statistics: an overview," *Statistics Surveys*, vol. 3, pp. 96–146, 2009.

[19] S. Benthall, "Situated information flow theory, situated information flow theory," *Association for Computing Machinery*, 2019.

[20] A. M. Adam, "Susceptibility of stock market returns to international economic policy: evidence from effective transfer entropy of Africa with the implication for open innovation," *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 6, no. 3, p. 71, 2020.

[21] A. M. Adam, E. N. Gyamfi, K. A. Kyei, S. Moyo, and R. S. Gill, "A new EEMD-effective transfer entropy-based methodology for exchange rate market information transmission in Southern Africa Development Community," *Complexity*, vol. 2021, Article ID 3096620, 2021.

[22] A. M. Adam, K. Kyei, S. Moyo, R. Gill, and E. N. Gyamfi, "Similarities in Southern African Development Community (SADC) exchange rate markets structure: evidence from the ensemble empirical mode decomposition," *Journal of African Business*, pp. 1–16, 2021.

[23] A. M. Adam, K. Kyei, S. Moyo, R. Gill, and E. N. Gyamfi, "Multifrequency network for SADC exchange rate markets using EEMD-based DCCA," *Journal of Economics and Finance*, 2021.

[24] E. Asafo-Adjei, P. Owusu Junior, and A. M. Adam, "Information Flow between Global Equities and Cryptocurrencies: A VMD-Based Entropy Evaluating Shocks from COVID-19 Pandemic," *Complexity*, vol. 2021, Article ID 4753753, 25 pages, 2021.

[25] A. Bossman, S. K. Agyei, P. Owusu Junior et al., "Flights-to-and-from-quality with Islamic and conventional bonds in the COVID-19 pandemic era: ICEEMDAN-based transfer entropy," *Complexity*, vol. 2022, pp. 1–25, 2022.

[26] G. Koutmos and G. G. Booth, "Asymmetric volatility transmission in international stock markets," *Journal of International Money and Finance*, vol. 14, no. 6, pp. 747–762, 1995.

[27] E. Asafo-Adjei, D. Agyapong, S. K. Agyei, S. Frimpong, R. Djimatey, and A. M. Adam, "Economic policy uncertainty and stock returns of Africa: a wavelet coherence analysis," *Discrete Dynamics in Nature and Society*, vol. 2020, pp. 1–8, 2020.

[28] E. Antwi, E. N. Gyamfi, K. Kyei, R. Gill, and A. M. Adam, "Determinants of commodity futures prices: decomposition approach," *Mathematical Problems in Engineering*, vol. 2021, 2021.

[29] K. Ijasan, G. Tweneboah, M. Omane-Adjepong, and P. Owusu Junior, "On the global integration of REITs market returns: a multiresolution analysis," *Cogent Economics and Finance*, vol. 7, no. 1, Article ID 1690211, 2019.

[30] K. Ijasan, P. Owusu Junior, G. Tweneboah, and A. M. Adam, "How does South Africa's real estate investment trusts integrate with major global REITs markets? A time-frequency approach," *Scientific African*, Article ID e00993, 2021a.

[31] K. Ijasan, P. Owusu Junior, G. Tweneboah, T. Oyedokun, and A. M. Adam, "Analysing the relationship between global REITs and exchange rates: fresh evidence from frequency-based quantile regressions," *Advances in Decision Sciences*, vol. 25, no. 3, pp. 58–91, 2021b.

[32] P. Owusu Junior, A. M. Adam, and G. Tweneboah, "Co-movement of real exchange rates in the west african monetary zone," *Cogent Economics and Finance*, vol. 5, no. 1, Article ID 1351807, 2017.

[33] P. Owusu Junior, B. Kwaku Boafo, B. Kwesi Awuye, K. Bonsu, and H. Obeng-Tawiah, "Co-movement of stock exchange indices and exchange rates in Ghana: a wavelet coherence analysis," *Cogent Business and Management*, vol. 5, no. 1, pp. 1–24, 2018.

[34] P. Owusu Junior, A. K. Tiwari, H. Padhan, and I. Alagidede, "Analysis of EEMD-based quantile-in-quantile approach on spot- futures prices of energy and precious metals in India," *Resources Policy*, vol. 68, Article ID 101731, 2020.

[35] P. Owusu Junior and G. Tweneboah, "Are there asymmetric linkages between African stocks and exchange rates?" *Research in International Business and Finance*, vol. 54, 2020.

[36] G. Tweneboah, P. Owusu Junior, and S. P. Kumah, "Modelling the asymmetric linkages between spot gold prices and African stocks," *Research in International Business and Finance*, vol. 54, Article ID 101246, 2020.

[37] D. Živkov, J. Njegić, and M. Pećanac, "Multiscale interdependence between the major agricultural commodities," *Agricultural Economics*, vol. 65, no. 2, pp. 82–92, 2019.

[38] P. Owusu Junior, G. Tweneboah, and A. M. Adam, "Interdependence of major exchange rates in Ghana: a wavelet coherence analysis," *Journal of African Business*, vol. 20, no. 3, pp. 407–430, 2019.

[39] G. Tweneboah, P. Owusu Junior, and E. K. Oseifuah, "Integration of major African stock markets: evidence from multi-scale wavelets correlation," *Academy of Accounting and Financial Studies Journal*, vol. 23, no. 6, pp. 1–15, 2019.

[40] N. E. Huang, Z. Shen, and S. R. Long, "A new view of nonlinear water waves: the Hilbert spectrum," *Annual Review of Fluid Mechanics*, vol. 31, no. 1, pp. 417–457, 1999.

[41] M. U. Rehman and X. V. Vo, "Energy commodities, precious metals and industrial metal markets: a nexus across different investment horizons and market conditions," *Resources Policy*, vol. 70, Article ID 101843, 2021.

[42] C. Su, X. Wang, and R. Tao, "Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context," *Energy*, vol. 172, pp. 691–701, 2019.

[43] E. Bouri, X. Lei, N. Jalkh, Y. Xu, and H. Zhang, "Spillovers in higher moments and jumps across US stock and strategic commodity markets," *Resources Policy*, vol. 72, Article ID 102060, 2021.

[44] M. Enilov, G. Fazio, and A. Ghoshray, "Global connectivity between commodity prices and national stock markets: a time-varying MIDAS analysis," *International Journal of Finance & Economics*, pp. 1–13, 2021.

[45] A. M. Karakas, A. Demir, and S. Calik, "Vine copula approach for modelling dependence of commodity and stock markets," *Journal of Statistics & Management Systems*, vol. 25, no. 1, pp. 1–21, 2022.

[46] T. L. D. Huynh, "The effect of uncertainty on the precious metals market: new insights from transfer entropy and neural network VAR," *Resources Policy*, vol. 66, Article ID 101623, 2020.

[47] A. Lahiani, D. K. Nguyen, and T. Vo, "Understanding return and volatility spillovers among major agricultural

commodities," *Journal of Applied Business Research*, vol. 29, no. 6, pp. 1781–1790, 2013.

[48] W. Mensi, S. Hammoudeh, D. K. Nguyen, and S. M. Yoon, "Dynamic spillovers among major energy and cereal commodity prices," *Energy Economics*, vol. 43, pp. 225–243, 2014.

[49] L. Baldi, M. Peri, and D. Vandone, "Stock markets' bubbles burst and volatility spillovers in agricultural commodity markets," *Research in International Business and Finance*, vol. 38, pp. 277–285, 2016.

[50] S. J. H. Shahzad, J. A. Hernandez, K. H. Al-Yahyaee, and R. Jammazi, "Asymmetric risk spillovers between oil and agricultural commodities," *Energy Policy*, vol. 118, pp. 182–198, 2018.

[51] E. M. Amrouk, S.-C. Grosche, and T. Heckelei, "Interdependence between cash crop and staple food international prices across periods of varying financial market stress," *Applied Economics*, vol. 52, no. 4, pp. 345–360, 2019.

[52] A. K. Tiwari, S. Nasreen, M. Shahbaz, and S. Hammoudeh, "Time-frequency causality and connectedness between international prices of energy, food, industry, agriculture and metals," *Energy Economics*, vol. 85, Article ID 104529, 2019.

[53] J. M. da Silva, M. G. Ferreira, Í. Barreto, T. Stosic, and B. Stosic, "Using transfer entropy to measure the information flow in sugar, ethanol and crude oil price series," *Publicacoes.Unifal-Mg.Edu.Br*, vol. 8, no. 2, pp. 405–410, 2019.

[54] I. Caglar and E. R. Hancock, "Network time series analysis using transfer entropy," in *Graph-Based Representations in Pattern Recognition*vol. Vol. 11510 LNCS, Manhattan, NY, USA, Springer International Publishing Cham, 2019.

[55] C. Liu, X. Sun, J. Wang, J. Li, and J. Chen, "Multiscale information transmission between commodity markets: an EMD-Based transfer entropy network," *Research in International Business and Finance*, vol. 55, Article ID 101318, 2021.

[56] H. Niu and Z. Hu, "Information transmission and entropy-based network between Chinese stock market and commodity futures market," *Resources Policy*, vol. 74, Article ID 102294, 2021.

[57] M. U. Rehman, E. Bouri, V. Eraslan, and S. Kumar, "Energy and non-energy commodities: an asymmetric approach towards portfolio diversification in the commodity market," *Resources Policy*, vol. 63, Article ID 101456, 2019.

[58] T. Mezghani, F. Ben Hamadou, and M. Boujelbène Abbes, "The dynamic network connectedness and hedging strategies across stock markets and commodities: COVID-19 pandemic effect," *Asia-Pacific Journal of Business Administration*, vol. 13, no. 4, pp. 520–552, 2021.

[59] J. Wang, F. Ma, E. Bouri, and J. Zhong, "Volatility of clean energy and natural gas, uncertainty indices, and global economic conditions," *Energy Economics*, vol. 108, Article ID 105904, 2022.

[60] N. Iqbal, E. Bouri, O. Grebinevych, and D. Roubaud, "Modelling extreme risk spillovers in the commodity markets around crisis periods including COVID19," *Annals of Operations Research*, Article ID 10479, 2022.

[61] P. Ferreira, D. Almeida, A. Dionísio, E. Bouri, and D. Quintino, "Energy markets - who are the influencers?" *Energy*, vol. 239, Article ID 121962, 2022.

[62] U. A. Müller, M. M. Dacorogna, R. D. Davé, O. V. Pictet, R. B. Olsen, and J. R. Ward, *Fractals and Intrinsic Time: A challenge to Econometricians*, Olsen & Associates, Jacksonville, Florida, USA, 1993.

[63] Y. Idilbi-Bayaa and M. Qadan, "Forecasting commodity prices using the term structure," *Journal of Risk and Financial Management*, vol. 14, no. 12, p. 585, 2021.

[64] Z. Umar, F. Jareño, and A. Escribano, "Dynamic return and volatility connectedness for dominant agricultural commodity markets during the COVID-19 pandemic era," *Applied Economics*, pp. 1–25, 2021.

[65] Z. Umar, Y. Riaz, and A. Zaremba, "Patterns of spillover in energy, agricultural, and metal markets: a connectedness analysis for years 1780-2020," *Finance Research Letters*, vol. 43, Article ID 101999, 2021.

[66] A. Zaremba, Z. Umar, and M. Mikutowski, "Commodity financialisation and price co-movement: lessons from two centuries of evidence," *Finance Research Letters*, vol. 38, Article ID 101492, 2021.

[67] S. I. Ivanov, "The influence of ETFs on the price discovery of gold, silver and oil," *Journal of Economics and Finance*, vol. 37, no. 3, pp. 453–462, 2013.

[68] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: a noise-assisted data analysis method," *Advances in Adaptive Data Analysis*, vol. 1, no. 01, pp. 1–41, 2009.

[69] P. J. J. Luukko, J. Helske, and E. Räsänen, "Introducing libeemd: a program package for performing the ensemble empirical mode decomposition," *Computational Statistics*, vol. 31, no. 2, pp. 545–557, 2016.

[70] R. V. L. Hartley, "Transmission of information 1," *Bell System Technical Journal*, vol. 7, no. 3, pp. 535–563, 1928.

[71] S. Behrendt, T. Dimpfl, F. J. Peter, and D. J. Zimmermann, "RTransferEntropy - quantifying information flow between different time series using effective transfer entropy," *Software*, vol. 10, Article ID 100265, 2019.

[72] T. Dimpfl and F. J. Peter, "Using transfer entropy to measure information flows between financial markets," *Studies in Nonlinear Dynamics and Econometrics*, vol. 17, no. 1, pp. 85–102, 2013.

[73] C. E. Shannon, "A mathematical theory of communication," *The Bell System Technical Journal*, vol. 27, no. 3, pp. 379–423, 1948.

[74] S. Kullback and R. A. Leibler, "On information and sufficiency," *The Annals of Mathematical Statistics*, vol. 22, pp. 79–86, 1951.

[75] A. Rényi, "On measures of entropy and information," in *Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Contributions to the Theory of Statistics*, pp. 547–561, Berkeley, CA, USA, January 1961.

[76] C. Beck and F. Schögl, *Thermodynamics of Chaotic Systems*, Berkeley, CA, USA, 1995.

[77] R. Marschinski and H. Kantz, "Analysing the information flow between financial time series," *The European Physical Journal B-Condensed Matter and Complex Systems*, vol. 30, no. 2, pp. 275–281, 2002.

[78] E. Bouri, B. Lucey, T. Saeed, and X. V. Vo, "The realized volatility of commodity futures: interconnectedness and determinants," *International Review of Economics & Finance*, vol. 73, pp. 139–151, 2021.

[79] C. Daskalaki, G. Skiadopoulos, and N. Topaloglou, "Diversification benefits of commodities: a stochastic dominance efficiency approach," *Journal of Empirical Finance*, vol. 44, pp. 250–269, 2017.

[80] B. Yang, Y. Sun, and S. Wang, "A novel two-stage approach for cryptocurrency analysis," *International Review of Financial Analysis*, vol. 72, Article ID 101567, 2020.

[81] P. Mongars and C. Marchal-Dombrat, "Commodities: An asset class in their own right? Bank of France," pp. 31–38, 2006, https://abc-economie.banque-france.fr/sites/default/files/medias/documents/financial-stability-review-09_2006-12.pdf#page=31.

[82] A. Levine, Y. H. Ooi, M. Richardson, and C. Sasseville, "Commodities for the long run," *Financial Analysts Journal*, vol. 74, no. 2, pp. 55–68, 2018.
[83] P. Ferreira, A. Dionísio, and G. F. Zebende, "Why does the Euro fail? The DCCA approach," *Physica A*, vol. 443, pp. 543–554, 2016.
[84] P. Ferreira, A. Dionísio, E. F. Guedes, and G. Zebende, "A sliding windows approach to analyse the evolution of bank shares in the European Union," *Physica A*, vol. 490, pp. 1355–1367, 2018.