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Research Article

ICEEMDAN-Based Transfer Entropy between Global Commodity Classes and African Equities

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We examine the information transfer dynamics between global commodity and African equity markets to test their efficiency levels in a denoised transfer entropy approach. Our findings in the short- and medium-term scales lend support to the alternative hypothesis of market efficiency, whereas the transfer entropies at the long-term scale lend support to the efficient market hypothesis and the long-term market efficiency. Investing in a single commodity results in high uncertainty when the return pattern (history) of African equities is acknowledged. Similarly, investing in any single African equity results in high return uncertainty whilst accounting for the history of commodity markets' returns. Short-term traders could monitor the loopholes in the market efficiency levels between global commodities and African equities to take advantage of arbitrage when needed, whilst long-term investors are assured of efficient market dynamics between global commodity markets and African equities. Regulation of markets may need to strategically incorporate news items as they fall due to either market.

1. Introduction

African economies are highly endowed with commodities, rendering several countries in the continent commodity-dependent. Unlike other assets, commodities markets are internationally regulated. Recent episodes of financial crises have caused several repercussions to international markets, motivating investors to create novel diversification opportunities [1, 2]. Commodities markets in Africa have been cautioned of their susceptibility to volatilities amid the COVID-19 pandemic [3]. Commodity prices have seen some hikes in recent periods, which means that vibrant commodity-producing and exporting economies may realise increased economic output and fiscal revenue. Notwithstanding, price volatility could lead to instability of the macroeconomy [4], which, in turn, could affect the potency of stock markets [5]. New alliances formed in the region also make the region susceptible to market integration, which hampers the resilience of African equity markets (AEMs).

African equities and global commodities are surrogates for international investors in terms of asset allocation. Although the recent conclusions of Zaremba et al. [6] cast doubt on the previously known facts about the financialisation hypothesis [7], should African equities get integrated amid the financialisation of global commodities, portfolio advantages for international portfolio management would most likely be wiped off. Capital flows into African economies would be significantly affected as a corollary to the extinction of diversification prospects for African equities [8]. To effectively assess the prospects for trading gains between markets, traders, regulators, and fund managers need information about the efficiency levels of markets to influence asset allocation, risk, and policy management, particularly in stressed market conditions where information flow and spillovers measure more than in normal trading conditions [2, 9, 10].

Distressed economic conditions impact stock market performance via the flow of information to investors, which then influences investor behaviour. It is through this channel that information flow also affects asset prices [11]. However, Fama [12, 13], through the efficient market hypothesis (EMH), contends that markets are expected to be efficient with any given information such that prices of assets wholly reflect prevailing information in the market and so no trader could benefit from a transaction based on the available information. Thus, privy to mutual information, global commodities, and AEMs are expected to respond similarly to information flow from each other. Therefore, in the wake of the commodity financialisation debate, financial market volatility, and the prospective integration of African markets, we argue that a quantification of the mutual information flow between global commodities and AEMs is a key input for managing portfolios and policies.

According to Mongars and Marchal-Dombrat [14], investors respond to commodity price and yield anomalies based on their investment timescale and the degree of diversification. Impliedly, cross-market connectedness is largely heterogeneous and hence should be studied as such. Empirical works on the issue of stock and commodity market linkages need to integrate multiscale analysis to ensure that the true relationships are revealed for the assets to aid efficient portfolio creation and management. Heterogeneous cross-market dynamics are traceable to the asymmetric, nonlinear, nonstationary, and noisy properties of financial economics time series [2, 15–18], and they partly explain why the degree, shape, and direction of variables' linkages have been long understood by economists to be timescale-dependent [19].

Unlike in the past when methods to demarcate economic datasets into all orthogonal timescale constituents were lacking, techniques are presently available. Thus, the instruments to cater for noise, which is usually transitory to economic data series, are accessible in present times [1, 16]. Therefore, based on the outlined issues of commodity market volatility and financialisation and the plausible integration of AEMs, we put the efficiency of global commodity and African equity markets' returns to the test in a novel Econophysics approach of a decomposition-based transfer entropy paradigm.

The latest strand of the crop of empirical modal decomposition (EMD), the improved form of the complete ensemble EMD (ICEEMDAN), from Huang [20], is a suitable technique that helps in studying nonlinear, asymmetric, and nonstationary signals whilst addressing the issues of residue noise and different modes generation, which are associated with earlier strands like the ensemble EMD, the complete ensemble EMD, and the complete ensemble EMD with adaptive noise [21]. These unique properties communicate the merits of ICEEMDAN, and as a corollary, the method has seen noteworthy applications in recent finance literature [1, 16, 22–24].

To provide an extremely novel approach to examining the efficiency of global commodity and African equity markets through the mutual information they share, the ICEEMDAN is employed to generate intramode functions (IMFs) that serve as inputs for quantifying information flow under the transfer entropy paradigm. Quantification of the mutual information between paired time series is facilitated by another Econophysics technique based on information transfer, which is measured using transfer entropy (TE). Schreiber [25] accentuates that TE is a theoretic quantification of information transfer from one market to another. The philosophical principles of Dretske [26] and the statistics of Pearl [27] facilitate the quantification of the situated information transferred between two markets, as hypothesised by Benthall [28]. With quantified information flows, we can determine the extent to which one variable (the recipient) observes the other (the transmitter) and vice versa [9].

If we could count on any relationship between two random variables such that one variable could study the state of the other through observation, then such a relationship is grounded on mutual information the variables share [28]. In the context of commodities and equities, the trading volumes, price volatilities, and investor sentiments are examples of mutual information shared by AEMs and global commodities [16]. Through the situated information flow theory, we could analyse how various commodities and African equities observe each other across different timescales. In this context, further assessments of market efficiency could be inferred. In line with Fama et al. [11] and Fama [12, 13], we expect that responding markets should bear similar responses to information flows to be deemed efficient. It is instructive to note that the application of the ICEEMDAN and transfer entropy methods in the context of assessing cross-market efficiency is nonexistent in the body of knowledge, particularly between global commodity and African equity markets.

We quantify the information transfer between global commodity and African equity markets' returns in a multiscale transfer entropy paradigm. We make significant contributions as follows. First, our study is distinct from the extant literature that examines the connectedness of commodity and equity markets with a focus on their comovements [29, 30] or spillovers [31–34]. We distinctly switch to the assessment of market efficiency between commodity and equity markets which is needed to inform market participants such as arbitragers, speculators, institutional investors, and market regulators. Knowledge about the information flow between these markets is essential to time-based decisions for all classes of investors.

Second, not only do we provide a unique assessment of cross-market connectedness, as there exist many in the extant literature, but also we focus on African markets, most of which are classified as emerging economies but have been largely ignored in terms of empirical investigations. These markets are essential because of their predictability of market returns which are especially vital for international portfolio construction. Besides, with the passage of recent episodes of financial crises, the fundamental attributes of African markets might have changed, as commodity financialisation is also gradually making commodities bear similar characteristics to traditional assets like stocks and bonds. Hence, we maintain that assessing the efficiency levels of global commodities and AEMs in a period full of market crises is timely.

Third, in the quest for policymakers' attempt to capitalise on their stock markets to attract capital flows into African economies, we provide an empirical analysis that allows them to monitor the efficiency levels of African stocks and global commodity markets based on the mutual information shared by these markets. The outcome of our empirical analysis should facilitate policy actions in African markets not only in a static or constant domain but also across trading horizons.

In terms of methods, we employ novel techniques that account for the nonhomogeneous characteristics of market participants. The ICEEMDAN offers IMFs from which short-, medium-, and long-term constituents of a signal could be deduced. These delineations enable us to provide sufficient evidence for time-based investors whose trading patterns resemble the short-, medium-, and long-term economic trading periods. In addition to the ICEEMDAN, the Rényi approach to transfer entropy (R-TE) is implemented in this study. The original strand of TE, the Shannon TE (S-TE), is inappropriate in our case because it fails to attribute equal weights to all probable expectations in a probability distribution [35]. Fat tails are pervasive in asset pricing, but S-TE does not overcome this assumption. R-TE uses a weighting value q to overcome the shortfall of S-TE.

From our findings, knowledge about African equity markets' history—in terms of returns—poses considerably more uncertainty to investors and market regulators than when the history of commodities only is incorporated. Our findings divulge high uncertainty with investment between African equity and global commodity markets across the short-, medium-, and long-term scales. We reveal that AEMs and global commodities are highly efficient across the long-term scale.

The remainder of the study is outlined as follows. We review related strands of empirical literature in Section 2. Section 3 presents the datasets and a discussion of the methodical frameworks. The main results are discussed in Section 4 with their implications in Section 5, and Section 6 concludes the study.

2. Literature Review

Recent literature on commodities, stocks, or commodity-stock nexus has gained focus owing to the reigning issue of commodity financialisation and the possible consequences. We review the main strands of works on this theme to contextualise our study.

These main strands discourse the dynamic interrelations between commodity classes only [36–40] and/or between commodities and traditional assets (like equities and exchange-traded funds (ETFs)) [41–43]. Undoubtedly, these works have been motivated fundamentally by high volatility in commodity markets and the issue of commodity financialisation, which still lingers in the empirical literature [6].

Specifically, in the first strand of works that examine the dynamic interdependencies between commodities classes, Tiwari et al. [36] examined long memory's persistence in petroleum and crude products from which the authors underscored weak (strong) efficiency in energy spot (Diesel Fuel) markets, with Propane lacking efficiency. Using the Generalised Hurst exponent method, the import of their study was the emphasis on the appropriateness of a dynamic model rather than static estimators. By employing datasets spanning over seven centuries, Umar et al. [37] identified high coherence between agricultural, energy, and industrial commodity groups. The authors stressed the leading role of energy across the time domain. When the TVP-VAR estimator was employed for the volatility and return series of precious metals amid the COVID-19 pandemic-induced global panic indices, the findings of Umar et al. [38] evidenced silver's resistance to global shocks, whilst the risk reduction roles of palladium and platinum were reported time-varying. With datasets on oil price shocks and agricultural commodities, Umar et al. [39] examined their volatility and return connectedness across the period between January 2002 and July 2020. Their findings—from the dynamic spillover index approach—divulged peaked connectedness in notable crisis periods such as the Global Financial Crisis, the European Sovereign debt, and the financial market meltdown in the era of the COVID-19 pandemic. The findings were similar to those reported by Umar et al. [40] who investigated the return and volatility linkages between crude oil and agricultural commodity markets under the TVP-VAR connectedness measure. As evidenced by their findings, the first strand of works emphasises the dynamic connectedness between commodity classes.

From the second strand of works, which evaluated the dynamic interrelations between commodity classes and other asset classes, Naeem et al. [42] examined the linkages between commodities and ETFs in a GARCH-based framework. Specifically, the authors explored the heterogeneous dependence between ETFs and crude oil. The findings emphasised the conclusions held by the first strand of works on commodity classes in the recent literature. Umar et al. investigated the link between crude oil shocks (risk, demand, and supply shocks) and equity markets of BRICS and GCC. The authors reported that the connectedness between oil shocks and equities is averagely moderate but measured high in the COVID-19 pandemic era. They emphasised the high influence of oil exporters' equities in their volatility connectedness with oil shocks. Esparcia et al. [41] revisited the safe-haven attribute of gold in a time-frequency paradigm covering the COVID-19 era. The basis for the study was to examine the role of gold in an equity-dominated portfolio using hybrid wavelet- and GARCH-based approaches. They added to the second strand of works by examining the cross-linkage between commodities and other asset classes (i.e., equities) from BRICS and G7 markets.

It is worthily noting that the two main strands of works on commodities and other asset classes are influenced partly by the recent strand of works which encompasses those pieces of literature focused on investigating the financialisation hypothesis and the plausible consequences to commodity-dominated or multiasset portfolios [6, 7, 44, 45]. Notwithstanding, the existing evidence is devoid of the links between African markets and global commodities. In terms of asset allocation, African stocks and global commodities are surrogates for foreign investors. Portfolio benefits for international portfolio management would very certainly be wiped out if African stocks were to become integrated during the financialisation of global commodities.

In the African context, Boako and Alagidede [29, 30] examined the connectedness of commodity and equity markets with a focus on their comovements, whereas Kablan et al. [46] focused on the link between commodity exporters' credit and commodities. From their analysis, these works draw no knowledge concerning the efficiency levels of commodity and equity markets. Thus, from the existing literature, the issue of market efficiency between commodity and equity markets is yet to be attended to. To provide evidence from the African context, we examine the information flow dynamics between African equities and global commodity classes. This is relevant to policymakers, investors, regulators, and practitioners. International investors who are interested in equities from emerging markets, such as those from Africa, stand to benefit because of the rising issues of commodity financialisation that compromises the safe-haven properties of some commodity investments. For policymakers and practitioners in Africa, the use of equity markets to attract capital flows can be effectively strategized when the mutual information transfer between international commodities and African equities is acknowledged.

Methodically, the use of transfer entropies, which quantifies the mutual information shared between financial markets, has gained attention in recent finance literature (see, e.g., [1, 9, 15, 16, 33, 47–50]). The relevance of entropy-based assessment of market efficiency is envisaged from the overflow of stressed market conditions in recent periods [50]. Tiwari et al. [36] found weak efficiency in energy spot markets, strong efficiency in Diesel Fuel markets, and an absence of efficiency with Propane markets when they examined long memory's persistence in petroleum and crude products. Their finding signals that the efficiency level of commodity markets could be based on the type of commodity. Similarly, out of financialisation, it is natural to expect that the cross-market efficiency levels, which emanate from commodity-dominated or multiasset portfolios [6], would differ between commodity types and/or classes.

Therefore, in providing evidence from the African context, we employ a transfer entropy-based approach to examine the efficiency levels of global commodity classes and African equity markets, focusing on major producers or exporters of various commodities in Africa.

3. Materials and Methods

3.1. Data. We utilise daily datasets—stock and commodity market indices—spanning from 22 February 2010 to 4 February 2022. A total of 13 African equity markets (Egypt, Ghana, Ivory Coast, Kenya, Malawi, Morocco, Namibia, Nigeria, South Africa, Tanzania, Uganda, Zambia, and Zimbabwe) are segregated into 12 commodity-based samples categorised into precious metals (gold, silver, palladium, and copper), softs (cocoa and coffee), grains (corn, rice, and soybeans), energies (crude oil and natural gas), and palm oil, which is unclassified in the broader categories of NASDAQ [51]. The choice of each sample was based on available stock market data for African countries. The constituent stock markets for the 12 commodity-based samples were determined by the major exporters of the various commodities in Africa. All data were supplied by EquityRT. The time-series plots for these samples are pictorially shown in Figure 1 with the numerical sample statistics in Table 1.

The observations for the various samples were numbered from 973 to 2022. All commodities recorded positive mean returns except corn. The return series portrays either mild or negative skewness, explaining why most of the stock markets recorded mean negative returns. The study period is filled with notable financial market meltdowns, and, hence, it is unsurprising that stock markets may—on average—record negative returns. This is also confirmatory of the results from the Jarque–Bera test of normality, in which all return series reject the hypothesis for normally distributed series. The return series for all the variables showed a leptokurtic character, which mimics the stylised fact about financial assets [52]. The stationarity properties of the return series were confirmed using the tests of Dickey and Fuller and Phillips and Perron, both of which proved that the return series are stationary at the 1% level of significance.

From Figure 1, as the raw series for the various indices indicate either peaks and troughs across crisis periods, the return series also display volatility clusters across diverse time and events. Notably, after experiencing peaks or troughs in crisis periods, the return series bounces back or assumes their fundamental behaviour [2].

3.2. Methodologies

3.2.1. ICEEMDAN. The latest strand of the EMD family-—the ICEEMDAN from Huang [20]—caters for noise that usually dominates the short term [16, 19]. Its strengths include efficiency, the noise-to-signal ratio (i.e., SNR), compression of modal decomposition in dynamic signals, and precision with reconstruction [1, 53]. The ICEEMDAN strand of Colominas et al. [54], which has the best of these properties, is summarised as follows:

Stage I: generate a new series by appending a white noise $\tau_1[\omega^{(i)}]$ to a signal α

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

where $\omega^{(i)}$ is the i-th white noise term added, ρ_0 denotes the SNR, and the number of added white noises is represented by N.

Stage II: estimate the local average of $\alpha^{(i)}$ by applying the EMD to glean the opening residual

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

from which the first IMF $c_1 = \alpha - r_1$ could be deduced.

Stage III: in a recursive process, generate the k-th IMF $c_k = r_{k-1} - r_k$, for $k \geq 2$, where

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

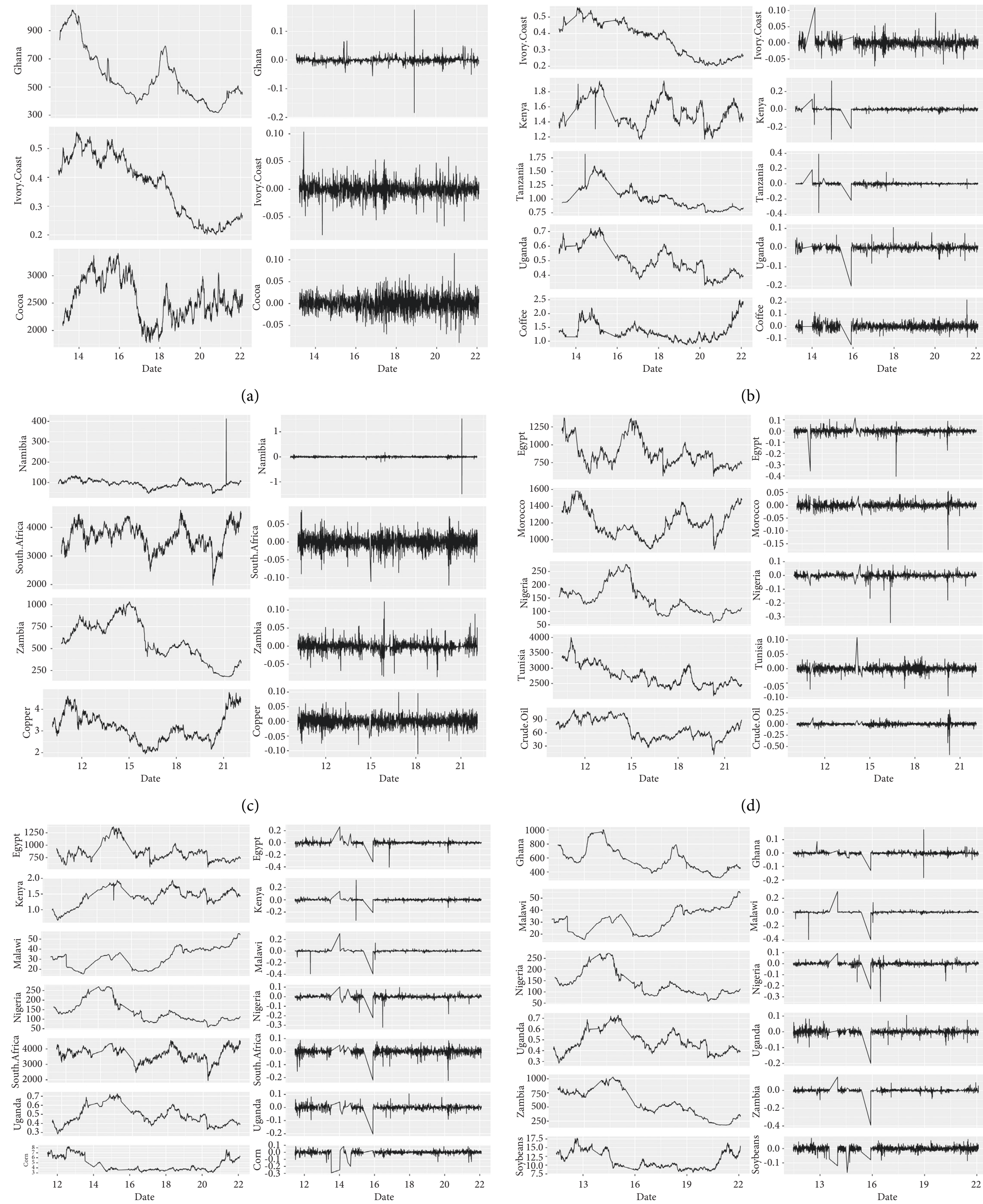
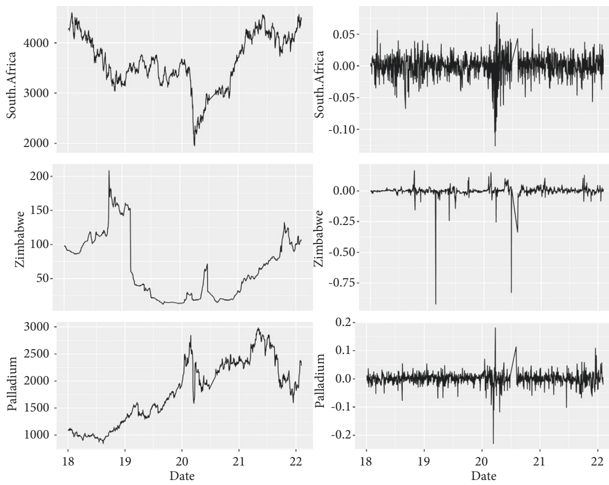


Figure 1: Continued.



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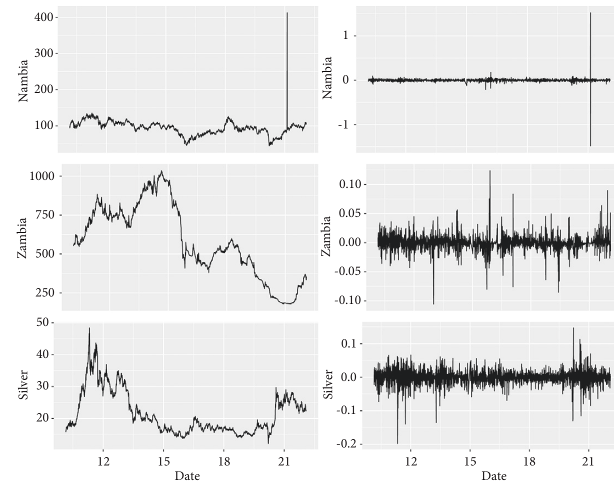

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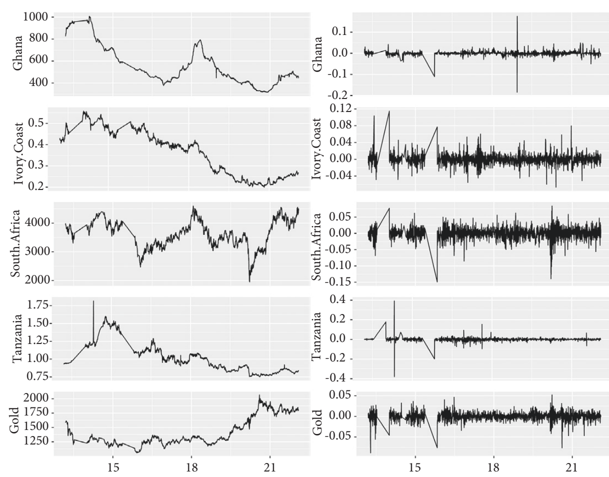

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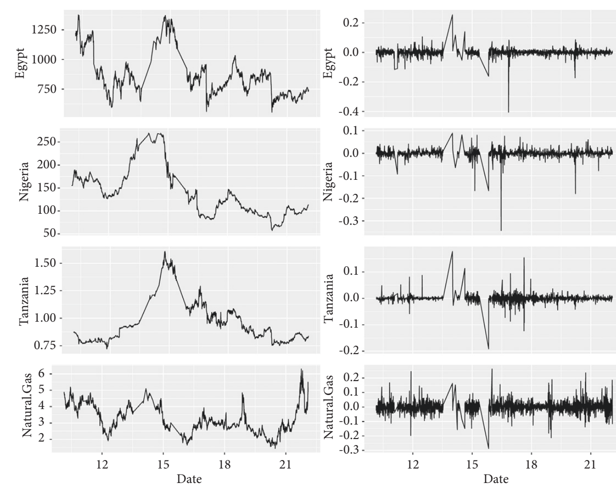

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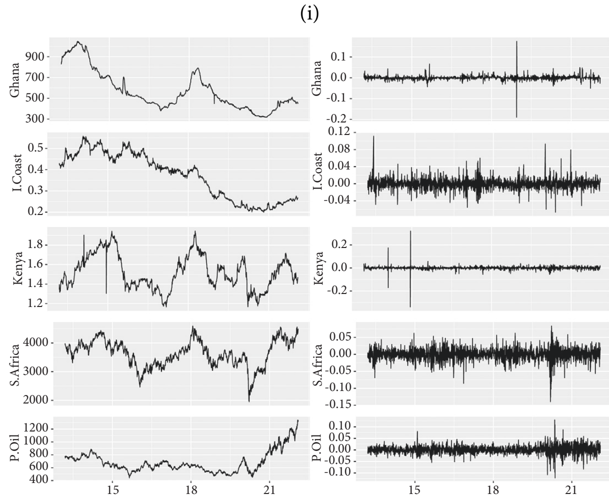

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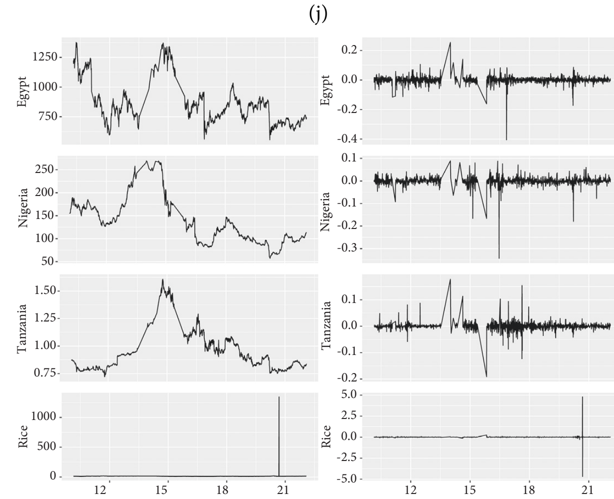


(l)

Figure 1: Time-series plots of stock and commodity indices and returns. (a) Cocoa sample, (b) coffee sample, (c) copper sample, (d) crude oil sample, (e) corn sample, (f) soybeans sample, (g) palladium sample, (h) silver sample, (i) gold sample, (j) natural gas sample, (k) palm oil sample, and (l) rice sample.

Table 1: Descriptive summary.

	Obs.	Min	Max	Mean	SD	Skewness	Kurtosis	Normtest.W	ADF	PP
Panel A: cocoa										
Ghana	1972	−0.1844	0.1750	−0.0003	0.0101	0.0652	104.8500	0.6661[a]	−17.528[a]	−48.7839[a]
Ivory Coast	1972	−0.0823	0.1036	−0.0002	0.0121	0.1671	6.4977	0.9370[a]	−46.8546[a]	−47.0482[a]
Cocoa	1972	−0.0890	0.1149	0.0001	0.0180	−0.0475	1.7259	0.9878[a]	−45.0131[a]	−45.0131[a]
Panel B: coffee										
Ivory Coast	1680	−0.0723	0.1091	−0.0003	0.0124	0.5190	8.4786	0.9190[a]	−43.6861[a]	−43.6501[a]
Kenya	1680	−0.3384	0.3205	0.0001	0.0173	−1.7359	184.4839	0.4779[a]	−49.6608[a]	−49.8064[a]
Tanzania	1680	−0.3807	0.3911	−0.0001	0.0190	0.2442	218.9706	0.4415[a]	−37.4915[a]	−58.0894[a]
Uganda	1680	−0.1995	0.1055	−0.0002	0.0126	−2.1530	44.1631	0.8072[a]	−38.2268[a]	−38.6505[a]
Coffee	1680	−0.1505	0.2180	0.0003	0.0239	0.5653	6.1437	0.9537[a]	−43.0812[a]	−43.0746[a]
Panel C: copper										
Namibia	2514	−1.4841	1.5234	0.000	0.0476	0.9116	787.6078	0.2793[a]	−38.9807[a]	−93.3737[a]
South Africa	2514	−0.1214	0.0891	0.0001	0.0179	−0.5405	3.6386	0.9646[a]	−49.6459[a]	−49.8784[a]
Zambia	2514	−0.0851	0.1234	−0.0002	0.0122	0.3057	12.1004	0.8648[a]	−41.7554[a]	−41.7409[a]
Copper	2514	−0.1109	0.0988	0.0001	0.0155	−0.1475	3.8851	0.9636[a]	−51.6736[a]	−51.7484[a]
Panel D: corn										
Egypt	1500	−0.4048	0.2659	−0.0002	0.0245	−3.7138	81.0439	0.6664[a]	−34.8129[a]	−34.6987[a]
Kenya	1500	−0.3384	0.3205	0.0002	0.0185	−1.6310	148.3292	0.5600[a]	−43.1659[a]	−43.0374[a]
Malawi	1500	−0.3944	0.3033	0.0003	0.0192	−8.9872	278.4907	0.2901[a]	−19.7749[a]	−39.7032[a]
Nigeria	1500	−0.3213	0.1037	−0.0002	0.0187	−5.3234	81.6910	0.6589[a]	−35.6957[a]	−36.3834[a]
South Africa	1500	−0.2240	0.0876	0.0001	0.0225	−1.9575	16.3399	0.8766[a]	−40.4411[a]	−40.4639[a]
Uganda	1500	−0.2022	0.1055	0.0000	0.0158	−1.5903	23.5141	0.8387[a]	−37.3765[a]	−37.7664[a]
Corn	1500	−0.2909	0.0858	−0.0001	0.0241	−2.9605	29.2003	0.7994[a]	−36.4454[a]	−36.3915[a]
Panel E: crude oil										
Egypt	2023	−0.4048	0.1170	−0.0002	0.0216	−5.8759	100.6912	0.7104[a]	−39.7403[a]	−39.4535[a]
Morocco	2023	−0.1732	0.0556	0.0000	0.0102	−2.4088	44.2860	0.8518[a]	−40.8932[a]	−40.8884[a]
Nigeria	2023	−0.3426	0.0812	−0.0002	0.0163	−5.8521	110.6448	0.6922[a]	−40.0702[a]	−40.7037[a]
Tunisia	2023	−0.0951	0.1086	−0.0002	0.0096	−0.1891	16.8704	0.8915[a]	−47.959[a]	−47.959[a]
Crude oil	2023	−0.6856	0.3196	0.0001	0.0358	−3.8484	84.6567	0.7053[a]	−24.5349[a]	−49.6916[a]
Panel F: gold										
Ghana	1765	−0.1844	0.1750	−0.0003	0.0103	−0.9313	111.4390	0.6378[a]	−17.5152[a]	−48.3704[a]
Ivory Coast	1765	−0.0663	0.1148	−0.0003	0.0126	1.0164	10.6749	0.8996[a]	−43.911[a]	−43.9843[a]
South Africa	1765	−0.1492	0.0840	0.0001	0.0182	−0.9988	7.6810	0.9333[a]	−43.4889[a]	−43.4889[a]
Tanzania	1765	−0.3807	0.3930	−0.0001	0.0186	0.4598	226.0898	0.4428[a]	−38.6487[a]	−60.0466[a]
Gold	1765	−0.0888	0.0525	0.0001	0.0101	−1.1150	9.7180	0.9124[a]	−40.8272[a]	−40.8123[a]
Panel G: natural gas										
Egypt	1880	−0.4048	0.2548	−0.0003	0.0222	−3.0051	74.0860	0.7287[a]	−38.0372[a]	−37.9597[a]
Nigeria	1880	−0.3426	0.0893	−0.0002	0.0171	−5.8108	103.1627	0.6708[a]	−38.6803[a]	−39.3506[a]
Tanzania	1880	−0.1907	0.1778	0.0000	0.0137	0.7186	56.4202	0.6514[a]	−53.2264[a]	−52.2806[a]
Natural gas	1880	−0.2866	0.2637	0.0000	0.0386	0.3514	7.6845	0.9118[a]	−46.9268[a]	−47.3475[a]
Panel H: palladium										
South Africa	973	−0.1264	0.0840	0.0001	0.0187	−0.8466	5.4978	0.9396[a]	−31.8417[a]	−31.8349[a]
Zimbabwe	973	−0.9230	0.1656	0.0001	0.0499	−11.6507	200.3893	0.3812[a]	−13.995[a]	−28.0297[a]
Palladium	973	−0.2298	0.1814	0.0008	0.0234	−0.7266	15.9859	0.8704[a]	−27.4854[a]	−27.3236[a]
Panel I: palm oil										
Ghana	1971	−0.1899	0.1750	−0.0003	0.0102	−0.2971	108.8040	0.6714[a]	−15.0156[a]	−49.813[a]
Ivory Coast	1971	−0.0663	0.1114	−0.0002	0.0122	0.6882	8.7048	0.9200[a]	−47.3046[a]	−47.416[a]
Kenya	1971	−0.3384	0.3205	0.0000	0.0153	−0.9127	234.9609	0.5133[a]	−55.1105[a]	−55.6653[a]
South Africa	1971	−0.1400	0.0840	0.0001	0.0178	−0.6833	5.2416	0.9544[a]	−46.3204[a]	−46.3017[a]
Palm oil	1971	−0.1219	0.1304	0.0003	0.0179	−0.1353	5.5025	0.9511[a]	−47.2528[a]	−47.2528[a]
Panel J: rice										
Egypt	1849	−0.4048	0.2548	−0.0003	0.0224	−2.9181	72.2304	0.7279[a]	−38.0794[a]	−38.0155[a]
Nigeria	1849	−0.3426	0.0893	−0.0002	0.0173	−5.6259	99.9010	0.6705[a]	−38.1888[a]	−38.8014[a]
Tanzania	1849	−0.1907	0.1778	0.0000	0.0139	0.8522	56.0470	0.6438[a]	−52.7263[a]	−51.8117[a]
Rice	1849	−4.6766	4.8092	0.0001	0.1575	1.2361	887.3842	0.0565[a]	−22.3664[a]	−309.259[a]
Panel K: silver										
Namibia	2724	−1.4841	1.5234	0.0000	0.0458	0.9491	852.4708	0.2763[a]	−40.5522[a]	−97.5834[a]
Zambia	2724	−0.1055	0.1234	−0.0002	0.0119	0.3309	14.1308	0.8546[a]	−44.8787[a]	−44.994[a]
Silver	2724	−0.1979	0.1472	0.0001	0.0195	−0.8753	10.8045	0.8996[a]	−38.5115[a]	−50.5268[a]

Table 1: Continued.

	Obs.	Min	Max	Mean	SD	Skewness	Kurtosis	Normtest.W	ADF	PP
					Panel L: soybeans					
Ghana	2022	−0.1844	0.1750	−0.0003	0.0104	−1.0241	104.6118	0.6534[a]	−18.6538[a]	−51.1332[a]
Malawi	2022	−0.3946	0.2992	0.0003	0.0164	−10.9823	393.8550	0.2505[a]	−44.9919[a]	−45.8344[a]
Nigeria	2022	−0.3426	0.0947	−0.0002	0.0158	−7.4810	143.8948	0.6165[a]	−40.091[a]	−40.8739[a]
Uganda	2022	−0.1995	0.1055	0.0000	0.0138	−1.5791	29.4339	0.8302[a]	−45.0267[a]	−45.3517[a]
Zambia	2022	−0.3908	0.1505	−0.0004	0.0149	−8.3849	239.6836	0.6076[a]	−41.7939[a]	−41.8346[a]
Soybeans	2022	−0.1668	0.0726	0.0001	0.0149	−1.4990	13.6953	0.9033[a]	−42.6755[a]	−42.6686[a]

Notes. [a]$p < 0.001$.

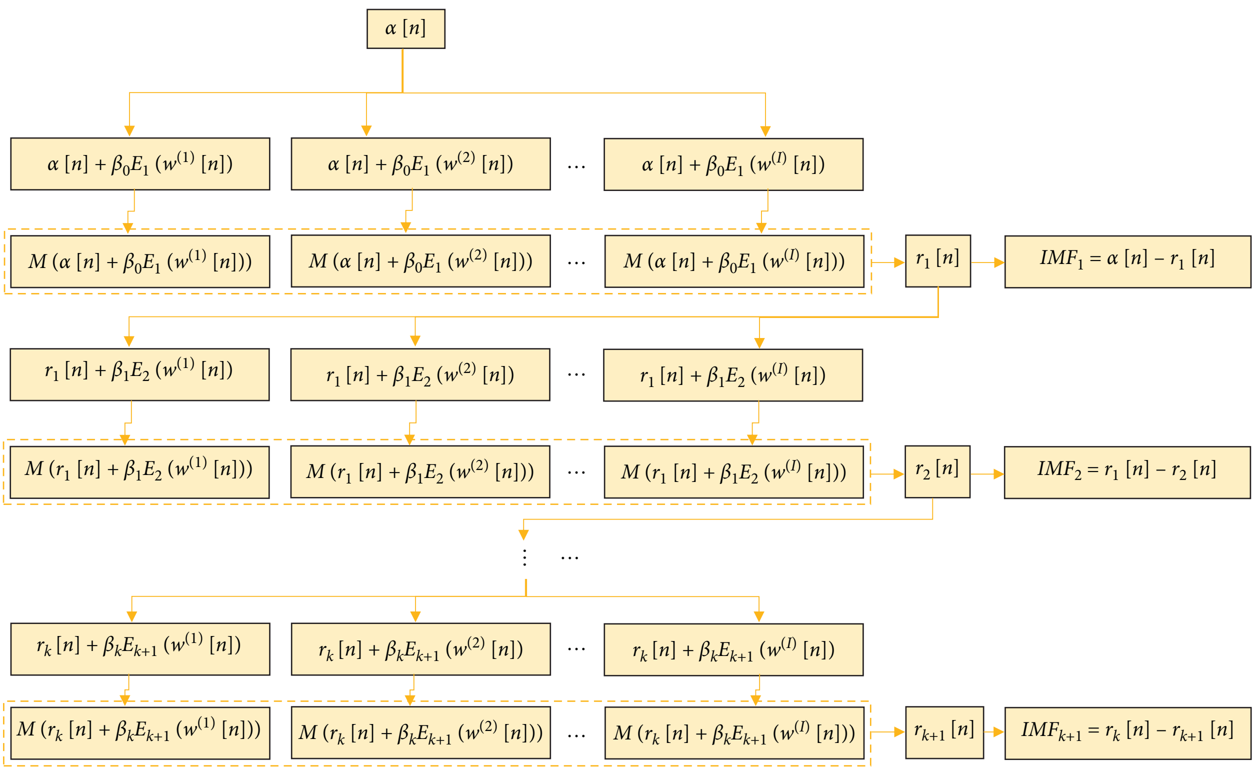


Figure 2: Flowchart of the ICEEMDAN algorithm [1, 16, 54].

We summarise the algorithm for ICEEMDAN in Figure 2. In line with existing works [55, 56], the number of IMFs and the selected IMFs to represent the short-, medium-, and long-term dynamics are presented in Table 2.

3.2.2. Rényi Transfer Entropy. 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

$$p\left(i_{t+1} | i_t, \ldots, i_{t-k+1}\right) = p\left(i_{t+1} | i_t, \ldots, i_{t-k}\right). \tag{4}$$

The mean bits needed for encoding the data point at $t+1$ after knowing k observations are given as

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

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 $p(i_{t+1}|i_t^{(k)}) = p(i_{t+1}|i_t^{(k)}, j_t^{(I)})$. Shannon entropy is then expressed as

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

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 $T_{I\longrightarrow J}$, which serves as the central information flow path.

The expediency of S-TE in the area of finance cannot be overemphasised, but it does not attribute equal weights

Table 2: Number of IMFs and selected IMFs from the ICEEMDAN algorithm.

	Number of IMFs	Selected IMFs
Panel A: cocoa		
Ghana	11	1, 5, 11
Ivory Coast	11	1, 5, 11
Cocoa	10	1, 5, 10
Panel B: coffee		
Ivory Coast	10	1, 5, 10
Kenya	10	1, 5, 10
Tanzania	11	1, 5, 11
Uganda	10	1, 5, 10
Coffee	10	1, 5, 10
Panel C: copper		
Namibia	12	1, 5, 12
South Africa	10	1, 5, 10
Zambia	11	1, 5, 11
Copper	10	1, 5, 10
Panel D: corn		
Egypt	10	1, 5, 10
Kenya	10	1, 5, 10
Malawi	11	1, 5, 11
Nigeria	11	1, 5, 11
South Africa	10	1, 5, 10
Uganda	11	1, 5, 11
Corn	12	1, 5, 12
Panel E: crude oil		
Egypt	11	1, 5, 11
Morocco	10	1, 5, 10
Nigeria	12	1, 5, 12
Tunisia	10	1, 5, 10
Crude oil	11	1, 5, 11
Panel F: gold		
Ghana	10	1, 5, 10
Ivory Coast	11	1, 5, 11
South Africa	10	1, 5, 10
Tanzania	11	1, 5, 11
Gold	11	1, 5, 11
Panel G: natural gas		
Egypt	11	1, 5, 11
Nigeria	12	1, 5, 12
Tanzania	11	1, 5, 11
Natural gas	11	1, 5, 11
Panel H: palladium		
South Africa	10	1, 5, 10
Zimbabwe	11	1, 5, 11
Palladium	9	1, 5, 9
Panel I: palm oil		
Ghana	10	1, 5, 10
Ivory Coast	10	1, 5, 10
Kenya	11	1, 5, 11
South Africa	11	1, 5, 11
Palm oil	10	1, 5, 10
Panel J: rice		
Egypt	11	1, 5, 11
Nigeria	12	1, 5, 12
Tanzania	12	1, 5, 12
Rice	11	1, 5, 11
Panel K: silver		
Namibia	11	1, 5, 11

Table 2: Continued.

	Number of IMFs	Selected IMFs
Zambia	11	1, 5, 11
Silver	10	1, 5, 10
Panel L: soybeans		
Ghana	11	1, 5, 11
Malawi	11	1, 5, 11
Nigeria	11	1, 5, 11
Uganda	11	1, 5, 11
Zambia	11	1, 5, 11
Soybeans	10	1, 5, 10

to all probable expectations in a probability distribution. Note that fat tails are pervasive in asset pricing, but S-TE does not overcome this assumption. Therefore, we resort to Rényi's [57] transfer entropy, which uses a weighting value q, to overcome the shortfall of S-TE. R-TE is computed as

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

with $q > 0$. For $q \longrightarrow 1$, R-TE and S-TE converge. For $0 < q < 1$, more weight is assigned to low probability events, whilst for $q > 1$, outputs j with higher initial probabilities are favoured by the weights. Resultantly, based on q, R-TE facilitates the assignment of different weights to unequal regions of the distribution [1, 35, 58]. This feature of R-TE makes it superior to S-TE and, hence, its desirability in finance.

The "escort distribution" $\varnothing_q(j) = p^q(j)/\sum_j p^q(j)$ for $q > 0$ is applied to normalise the weighted distributions [59], from which R-TE is estimated as

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

Note that negative estimates could be provided by the R-TE. Acknowledging J's record, in this case, connotes significantly more uncertainty than acknowledging only I's record would imply.

TE estimations are subject to biases in small samples [60]. The effective transfer entropy (i.e., ETE) can resolve this and is derived as

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

where the TE using faltered forms of the data series J is represented as $T_{Jshuffle\ d\longrightarrow I}(k,l)$. 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. We utilise the package "RTransferEntropy" in R programming.

4. Empirical Results

4.1. Multiscale Analysis of Transfer Entropies. We examine the causal influence between global commodities and African stock market returns. Fat tails are pervasive in asset pricing and need to be accounted for. As a result, within the confidence bound of 95%, we use Rényi's TE approach by specifying a weighting value $q = 0.30$, which helps to account for fat tails [2, 16, 22].

We follow the extant literature to represent the short term with IMF_1, the medium term with IMF_5, and the long term with the residual IMF [55, 56]. Estimation results are detailed in Figures 3–6 (with numerical ETEs in Table 3) (the ETEs for the remaining IMFs are quantitatively similar and are available upon request.). ETEs for signal (composite) and IMFs are both reported for comparison. Frequency-domain (signal/composite) ETEs are demonstrated by black dots located in blue (red) bars. The ends of blue or red bars represent the 95% confidence bounds. Therefore, the hypothesis of "no information flow" is not supported by any confidence bounds that fully fit in either the positive or negative region. ETEs are statistically nonsignificant if the confidence boundaries cross the origin. High-risk (low-risk) assets are depicted by negative (positive) ETEs.

From Figure 3, the composite or signal ETEs show differing directions, magnitudes, and significance. Information flow between commodities and equities for the samples cocoa, copper, natural gas, palladium, and silver samples are statistically insignificant. For the coffee sample, Tanzania (Kenya) receives negative information flow from the coffee market. Uganda and Ivory Coast transmit negative flow towards coffee. Thus, the results communicate high uncertainties in African stock returns when the coffee market is hit by a crisis. Nigeria is the only market that receives significant flow from corn at the composite level. The Egyptian market receives (transmits) negative flow from (towards) crude oil, suggesting that the information flow between crude oil and stock markets' returns is bidirectional. The Moroccan and Nigerian markets also transmit significant negative flow to the crude oil market returns.

From the gold sample, the South African (Ivorian) market receives (transmits) negative flows from (towards) gold returns. The bidirectional interplay of information flow found for the crude oil sample also holds for palm oil, where Kenya is both a receiver and transmitter of negative ETE. For the rice sample, when shocks befall the rice market, the Egyptian and Tanzanian stock markets are negatively affected, but the same does not hold when shocks befall the stock markets and, hence, makes investments in the Egyptian and Tanzanian markets more uncertain. Zambia receives a negative ETE from soybeans whilst Ghana receives a positive ETE.

Although the signal (composite) ETEs are important to examine how each variable learns the state of the other through observation [28], it conceals relevant information that may be relevant for time-based investors. Therefore, the frequency-domain ETEs are further analysed.

Figure 4 depicts the short-term ETEs from which we find that Kenya and Ivory Coast receive negative ETEs from coffee. Namibia (Egypt) responds negatively to information flow from copper (corn) in the short term. The bidirectional interplay between crude oil and stocks is strengthened in the short term, as shown by the increased number of negative ETE transmissions between crude oil and the stock markets of Morocco, Egypt, and Nigeria in the short term. The signal ETEs only reveal Egypt as the significant variable, but the frequency-domain ETEs unravel the potential of additional markets. This further substantiates the need for frequency-domain analysis, as employed in this study.

Bicausality is also found for the ETEs between South Africa and gold and Zambia and soybeans in the short term. Egypt (Nigeria) receives (transmits) negative flows from (towards) natural gas in the short term. South Africa (Nigeria) receives (transmits) negative flows from (towards) palladium (rice), whilst Uganda and Malawi also receive negative flows from soybeans. The number of negative ETEs increases in the short term, indicating that returns from equities markets stand high uncertainties given shocks from their respective dominant commodity markets.

The transmission of ETEs in the medium term is depicted in Figure 5. From the cocoa sample, the negative ETE recipient status of Ivory Coast was found significant in the medium term; meanwhile, it was insignificant at the signal or composite level. Kenya and Uganda (Ivory Coast) receive (transmit) negative flows from (towards) coffee in the medium term. Malawi (South Africa) is a negative ETE recipient (transmitter) from (towards) the corn sample. In the medium term, Nigeria, Tunisia, and Morocco receive negative ETEs from crude oil with Morocco also transmitting negative flows to crude oil. The findings reignite the bidirectional causality in the case of crude oil. Ivory Coast and Tunisia receive negative ETEs from gold whilst South Africa transmits a negative ETE to gold.

Egypt and Tanzania (Egypt and Nigeria) receive (transmit) negative ETEs from (towards) natural gas. The bidirectional (bicausality) interplay is once again revealed between the Egyptian and natural gas ETEs. This is the same as the case of the ETEs between Zambia and palladium, Namibia and silver, and Malawi and soybeans, all in the medium term. It is important to note that we find that South Africa (Tanzania) transmits a negative ETE towards palladium (rice), whilst Ivory Coast, Ghana, and South Africa all transmit negative flows towards palm oil. From the silver sample, when shocks befall the equities markets of dominant African silver producers or exporters, Namibia transmits a negative ETE to silver, whilst Zambia transmits a positive ETE to silver. With the high and low-risk status of Namibia and Zambia, respectively, they could serve as diversifiers for one another during such a market condition. A similar observation holds for the soybeans sample between Malawi (high risk) and Uganda (low risk) in the medium term.

The ETEs between residual IMFs for equities and commodity markets are detailed in Figure 6. Virtually all ETEs are negative in the long term. South Africa and Zambia reveal exceptional positive ETEs in the palladium and silver samples, respectively, all of which are insignificant. Aside from these exceptional nonsignificant ETEs, all other ETEs from all commodity-based samples in the long term were

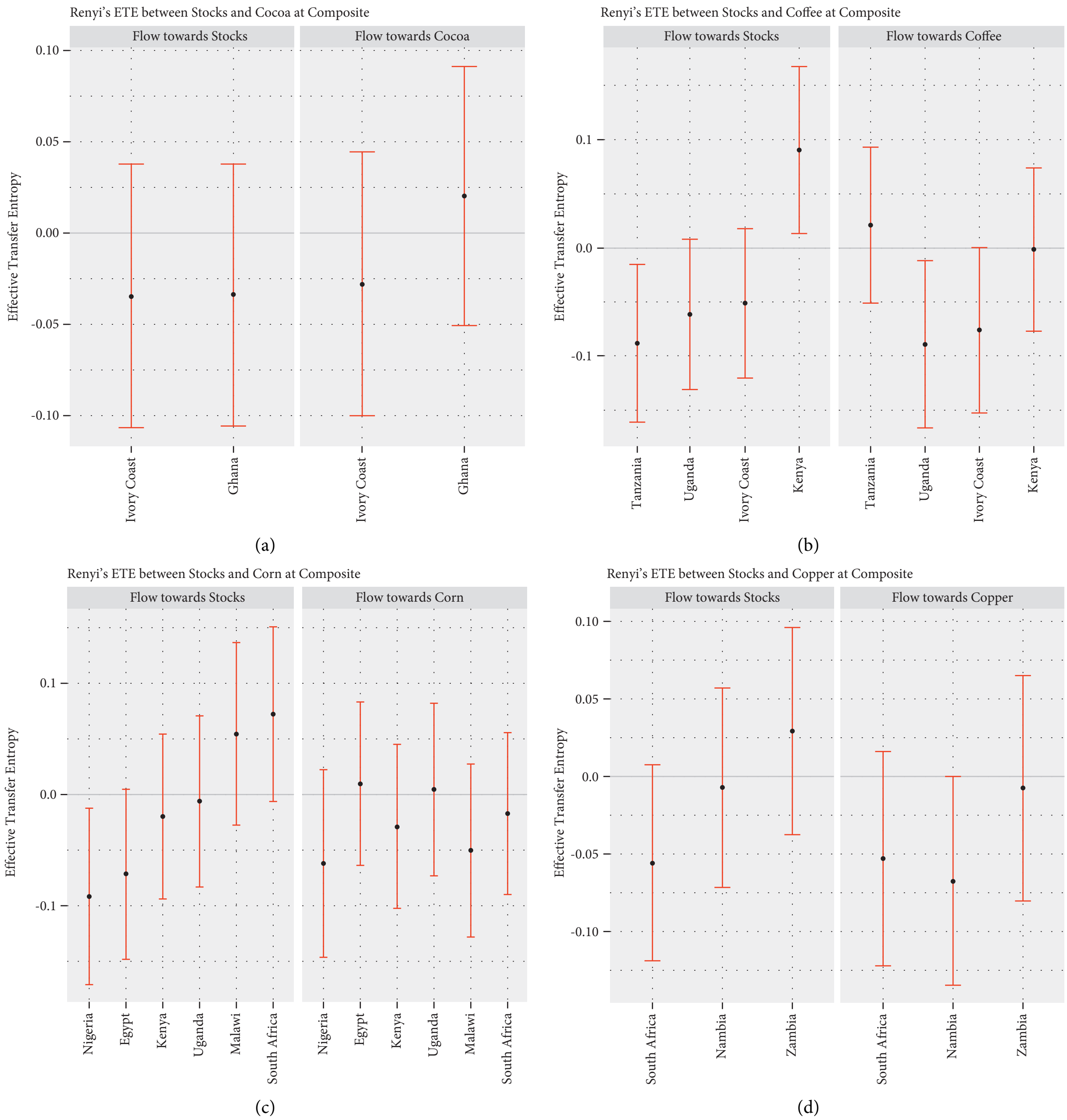
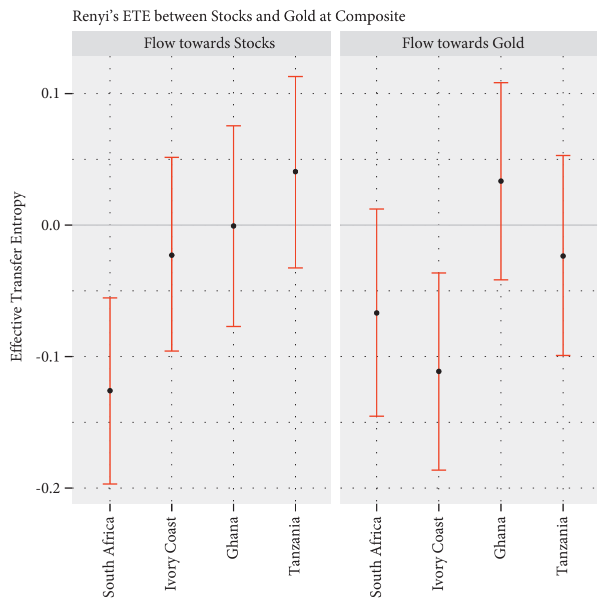


Figure 3: Continued.



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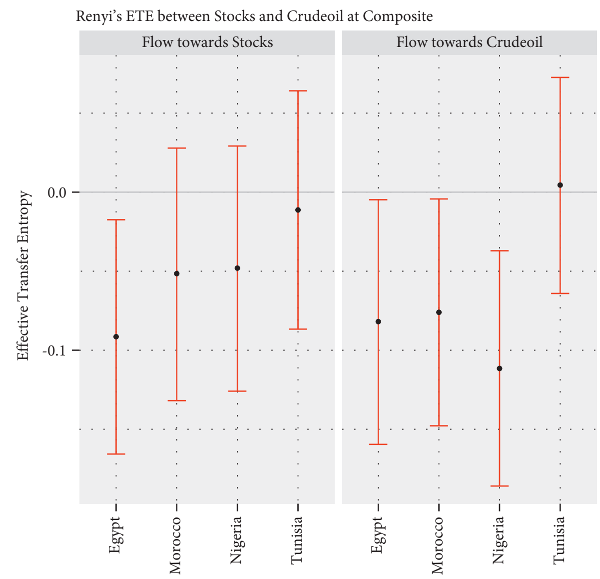

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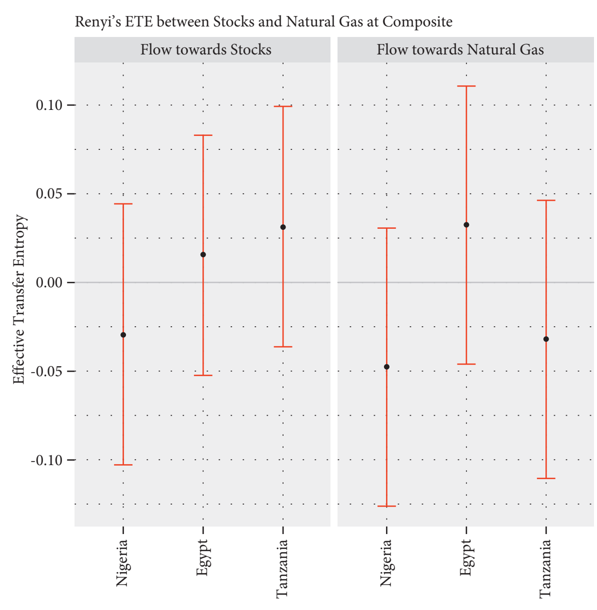

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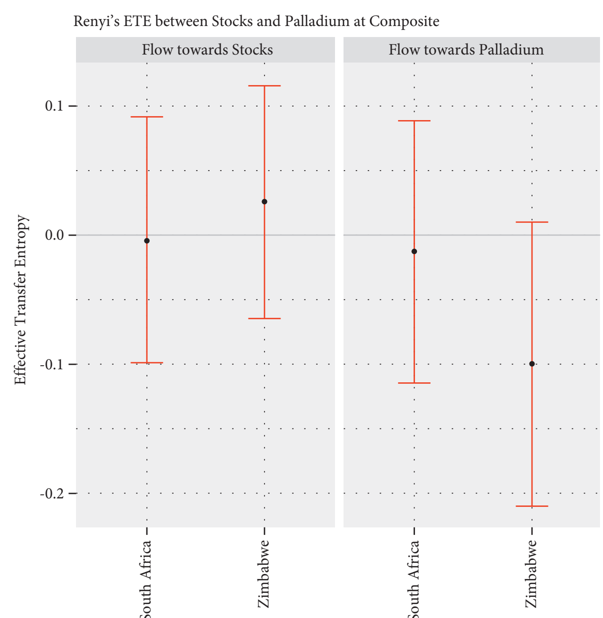

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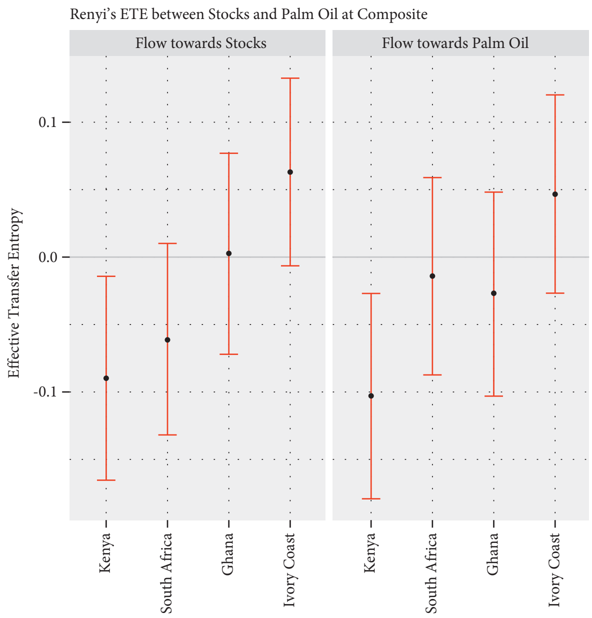
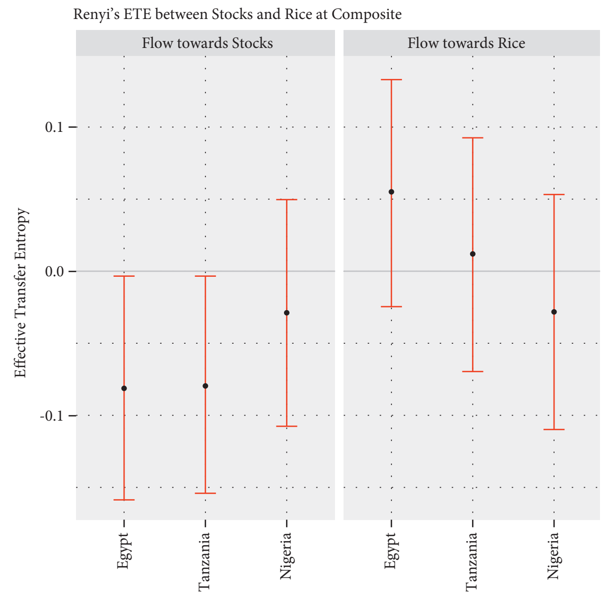
Figure 3: Continued.



(i)



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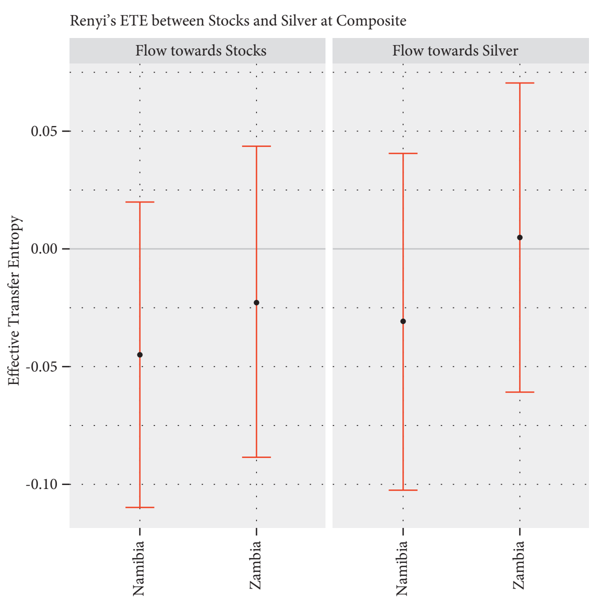

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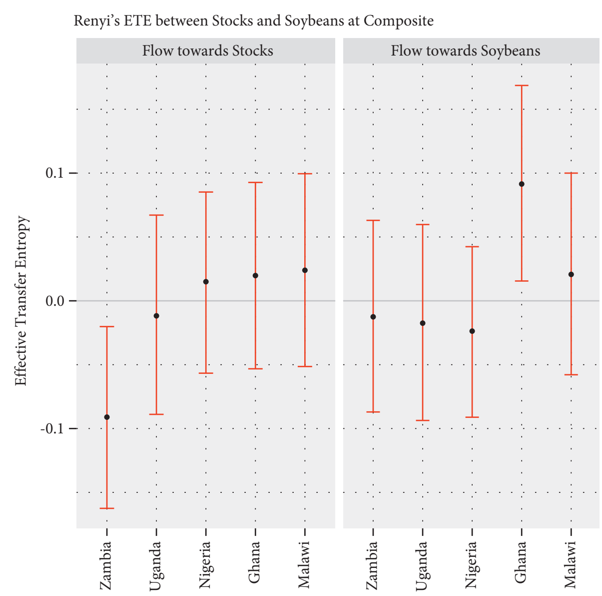


(l)

Figure 3: Signal ETEs between stock and commodity markets' returns.

Table 3: Numerical ETEs.

Market	Direction	Signal/composite			IMF1 (short term)			IMF5 (medium term)			Residual IMF (long term)		
		β	SE	t-stats	β	SE	t-stats	β	SE	t-stats	β	SE	t-stats
Panel A: cocoa sample													
Ghana	Cocoa->stocks	−0.0339	0.0435	−0.7801	−0.0458	0.0496	−0.9236	0.0529	0.0600	0.8810	−0.0293	0.0436	−0.6713
Ghana	Stocks->cocoa	0.0203	0.0430	0.4732	0.0848	0.0567	1.4961	−0.0218	0.0554	−0.3935	−0.0401	0.0358	−1.1206
Ivory Coast	Cocoa->stocks	−0.0344	0.0439	−0.7838	−0.0196	0.0498	−0.3928	−0.1445	0.0529	−2.7317	−0.0296	0.0431	−0.6861
Ivory Coast	Stocks->cocoa	−0.0278	0.0439	−0.6336	0.0151	0.0571	0.2643	−0.0027	0.0545	−0.0490	−0.0550	0.0225	−2.4454
Panel B: coffee sample													
Ivory Coast	Coffee->stocks	−0.0512	0.0417	−1.2291	−0.0932	0.0540	−1.7256	−0.0671	0.0552	−1.2155	−0.0379	0.0431	−0.8787
Ivory Coast	Stocks->coffee	−0.0768	0.0464	−1.6546	−0.0390	0.0607	−0.6427	−0.1341	0.0579	−2.3164	−0.0436	0.0514	−0.8476
Kenya	Coffee->stocks	0.0902	0.0469	1.9216	−0.0942	0.0558	−1.6873	−0.1151	0.0543	−2.1175	−0.0588	0.0462	−1.2712
Kenya	Stocks->coffee	−0.0017	0.0458	−0.0368	−0.0872	0.0690	−1.2625	−0.0658	0.0589	−1.1168	−0.0578	0.0424	−1.3626
Tanzania	Coffee->stocks	−0.0886	0.0442	−2.0028	−0.0872	0.0555	−1.5718	−0.0109	0.0563	−0.1933	−0.0369	0.0423	−0.8730
Tanzania	Stocks->coffee	0.0211	0.0438	0.4828	−0.0439	0.0690	−0.6356	−0.0283	0.0565	−0.5015	−0.0432	0.0513	−0.8416
Uganda	Coffee->stocks	−0.0618	0.0421	−1.4679	−0.0436	0.0554	−0.7859	−0.1137	0.0557	−2.0411	−0.0544	0.0404	−1.3460
Uganda	Stocks->coffee	−0.0896	0.0470	−1.9074	−0.0784	0.0640	−1.2242	−0.0488	0.0620	−0.7873	−0.0472	0.0458	−1.0315
Panel C: copper sample													
Namibia	Copper->stocks	−0.0071	0.0393	−0.1811	−0.1047	0.0445	−2.3531	−0.0456	0.0562	−0.8113	−0.0529	0.0460	−1.1500
Namibia	Stocks->copper	−0.0672	0.0408	−1.6456	−0.0296	0.0553	−0.5343	−0.0712	0.0554	−1.2848	−0.0771	0.0199	−3.8685
South Africa	Copper->stocks	−0.0557	0.0385	−1.4456	−0.0615	0.0433	−1.4200	−0.0819	0.0549	−1.4929	−0.0522	0.0466	−1.1215
South Africa	Stocks->copper	−0.0528	0.0420	−1.2595	−0.0318	0.0434	−0.7338	−0.0063	0.0573	−0.1094	−0.0404	0.0381	−1.0596
Zambia	Copper->stocks	0.0295	0.0405	0.7278	−0.0513	0.0444	−1.1568	−0.0925	0.0591	−1.5656	−0.0532	0.0463	−1.1488
Zambia	Stocks->copper	−0.0076	0.0442	−0.1712	−0.0299	0.0493	−0.6074	−0.0501	0.0532	−0.9405	−0.0773	0.0207	−3.7395
Panel D: corn sample													
Egypt	Corn->stocks	−0.0721	0.0465	−1.5504	−0.1153	0.0658	−1.7536	−0.0200	0.0574	−0.3488	−0.0592	0.0405	−1.4632
Egypt	Stocks->corn	0.0093	0.0446	0.2085	−0.0952	0.0696	−1.3674	−0.0687	0.0580	−1.1851	−0.0467	0.0438	−1.0660
Kenya	Corn->stocks	−0.0203	0.0451	−0.4511	−0.0799	0.0682	−1.1714	0.0611	0.0585	1.0432	−0.0471	0.0393	−1.1974
Kenya	Stocks->corn	−0.0291	0.0451	−0.6458	−0.0322	0.0693	−0.4651	0.0475	0.0624	0.7618	−0.0456	0.0501	−0.9097
Malawi	Corn->stocks	0.0542	0.0496	1.0925	−0.0259	0.0634	−0.4091	−0.1122	0.0579	−1.9370	−0.0610	0.0386	−1.5790
Malawi	Stocks->corn	−0.0510	0.0473	−1.0772	−0.1169	0.0757	−1.5446	−0.0348	0.0590	−0.5894	−0.0877	0.0228	−3.8530
Nigeria	Corn->stocks	−0.0920	0.0481	−1.9124	−0.0915	0.0681	−1.3439	0.0216	0.0565	0.3823	−0.0611	0.0387	−1.5807
Nigeria	Stocks->corn	−0.0623	0.0514	−1.2122	−0.0924	0.0719	−1.2856	−0.0685	0.0554	−1.2367	−0.0874	0.0232	−3.7640
South Africa	Corn->stocks	0.0723	0.0477	1.5145	0.0032	0.0707	0.0447	0.0666	0.0545	1.2216	−0.0303	0.0398	−0.7614
South Africa	Stocks->corn	−0.0178	0.0443	−0.4025	−0.0349	0.0621	−0.5628	−0.1014	0.0529	−1.9172	−0.0288	0.0510	−0.5646
Uganda	Corn->stocks	−0.0064	0.0468	−0.1358	−0.1056	0.0678	−1.5566	−0.0853	0.0565	−1.5117	−0.0452	0.0387	−1.1695
Uganda	Stocks->corn	0.0044	0.0471	0.0926	−0.0815	0.0685	−1.1903	−0.0403	0.0585	−0.6878	−0.0449	0.0526	−0.8550
Panel E: crude oil sample													
Egypt	Crude oil->stocks	−0.0914	0.0450	−2.0328	−0.1222	0.0611	−1.9996	−0.0860	0.0545	−1.5767	−0.0818	0.0359	−2.2765
Egypt	Stocks->crude oil	−0.0819	0.0472	−1.7356	−0.1447	0.0676	−2.1402	−0.0705	0.0581	−1.2126	−0.0815	0.0360	−2.2626
Morocco	Crude oil->stocks	−0.0520	0.0485	−1.0727	−0.1266	0.0598	−2.1177	−0.1510	0.0542	−2.7858	−0.0692	0.0349	−1.9827
Morocco	Stocks->crude oil	−0.0760	0.0433	−1.7538	−0.1019	0.0570	−1.7868	−0.1346	0.0552	−2.4383	−0.0763	0.0348	−2.1903
Nigeria	Crude oil->stocks	−0.0482	0.0472	−1.0212	−0.1117	0.0569	−1.9614	−0.1228	0.0567	−2.1657	−0.0564	0.0348	−1.6208
Nigeria	Stocks->crude oil	−0.1112	0.0450	−2.4713	−0.1125	0.0622	−1.8092	0.0434	0.0575	0.7555	−0.0812	0.0228	−3.5580
Tunisia	Crude oil->stocks	−0.0114	0.0456	−0.2493	−0.0502	0.0617	−0.8141	−0.1519	0.0548	−2.7706	−0.0560	0.0357	−1.5669
Tunisia	Stocks->crude oil	0.0043	0.0416	0.1028	−0.0202	0.0544	−0.3715	−0.0188	0.0566	−0.3323	−0.0811	0.0225	−3.6040
Panel F: gold sample													
Ghana	Gold->stocks	−0.0004	0.0463	−0.0083	−0.0203	0.0634	−0.3196	0.0050	0.0614	0.0809	−0.0581	0.0484	−1.2005
Ghana	Stocks->gold	0.0334	0.0453	0.7378	0.0385	0.0627	0.6138	−0.0049	0.0615	−0.0800	−0.0850	0.0220	−3.8660
Ivory Coast	Gold->stocks	−0.0224	0.0445	−0.5023	−0.0444	0.0640	−0.6935	−0.1627	0.0600	−2.7135	−0.0582	0.0497	−1.1706
Ivory Coast	Stocks->gold	−0.1110	0.0454	−2.4426	−0.0984	0.0615	−1.5997	−0.0330	0.0624	−0.5299	−0.0856	0.0214	−3.9954
South Africa	Gold->stocks	−0.1258	0.0428	−2.9361	−0.1304	0.0601	−2.1698	−0.0707	0.0585	−1.2070	−0.0581	0.0484	−1.2019
South Africa	Stocks->gold	−0.0669	0.0479	−1.3958	−0.1601	0.0602	−2.6583	−0.1988	0.0545	−3.6462	−0.0846	0.0226	−3.7395
Tanzania	Gold->stocks	0.0404	0.0442	0.9133	−0.0561	0.0607	−0.9236	−0.1334	0.0561	−2.3795	−0.0838	0.0470	−1.7826
Tanzania	Stocks->gold	−0.0232	0.0462	−0.5026	0.0118	0.0671	0.1751	−0.0088	0.0599	−0.1476	−0.0842	0.0492	−1.7101
Panel G: natural gas sample													
Egypt	Natural gas->stocks	0.0154	0.0412	0.3730	−0.1336	0.0586	−2.2821	−0.1690	0.0562	−3.0083	−0.0431	0.0490	−0.8797
Egypt	Stocks->natural gas	0.0326	0.0482	0.6754	−0.0657	0.0681	−0.9646	−0.1464	0.0572	−2.5601	−0.0648	0.0231	−2.8029
Nigeria	Natural gas->stocks	−0.0296	0.0448	−0.6616	0.0271	0.0558	0.4850	−0.0026	0.0565	−0.0451	−0.0432	0.0491	−0.8795
Nigeria	Stocks->natural gas	−0.0478	0.0476	−1.0036	−0.1284	0.0598	−2.1474	−0.1000	0.0609	−1.6429	−0.0657	0.0221	−2.9717
Tanzania	Natural gas->stocks	0.0315	0.0412	0.7636	−0.0488	0.0592	−0.8241	−0.1003	0.0579	−1.7308	−0.0463	0.0486	−0.9527
Tanzania	Stocks->natural gas	−0.0319	0.0475	−0.6730	−0.0137	0.0636	−0.2150	0.0292	0.0602	0.4846	−0.0417	0.0421	−0.9906
Panel H: palladium sample													
South Africa	Palladium->stocks	−0.0041	0.0580	−0.0709	−0.1290	0.0735	−1.7560	0.0094	0.0539	0.1745	−0.0793	0.0445	−1.7838
South Africa	Stocks->palladium	−0.0127	0.0620	−0.2047	−0.0379	0.0689	−0.5496	−0.1664	0.0510	−3.2633	0.0222	0.0419	0.5294
Zimbabwe	Palladium->stocks	0.0254	0.0550	0.4612	−0.0119	0.0749	−0.1587	−0.1037	0.0516	−2.0101	−0.0317	0.0430	−0.7375
Zimbabwe	Stocks->palladium	−0.1002	0.0670	−1.4956	−0.1011	0.0762	−1.3262	−0.1204	0.0582	−2.0702	−0.0746	0.0281	−2.6515

Table 3: Continued.

Market	Direction	Signal/composite			IMF1 (short term)			IMF5 (medium term)			Residual IMF (long term)		
		β	SE	t-stats	β	SE	t-stats	β	SE	t-stats	β	SE	t-stats
Panel I: palm oil sample													
Ghana	Palm oil->stocks	0.0024	0.0455	0.0536	−0.0596	0.0588	−1.0143	0.0078	0.0581	0.1350	−0.0814	0.0349	−2.3307
Ghana	Stocks->palm oil	−0.0274	0.0462	−0.5917	−0.1121	0.0569	−1.9685	−0.1130	0.0572	−1.9763	−0.0821	0.0371	−2.2141
Ivory Coast	Palm oil->stocks	0.0633	0.0424	1.4937	−0.0346	0.0568	−0.6089	−0.0827	0.0584	−1.4166	−0.0279	0.0346	−0.8053
Ivory Coast	Stocks->palm oil	0.0464	0.0449	1.0321	−0.0973	0.0599	−1.6226	−0.1126	0.0574	−1.9610	−0.0269	0.0485	−0.5551
Kenya	Palm oil->stocks	−0.0901	0.0458	−1.9689	−0.1149	0.0597	−1.9240	0.0108	0.0600	0.1805	−0.0276	0.0365	−0.7563
Kenya	Stocks->palm oil	−0.1034	0.0463	−2.2339	−0.0278	0.0573	−0.4856	−0.0651	0.0576	−1.1308	−0.0263	0.0469	−0.5605
South Africa	Palm oil->stocks	−0.0613	0.0433	−1.4161	−0.0968	0.0591	−1.6368	−0.0341	0.0587	−0.5804	−0.0421	0.0364	−1.1560
South Africa	Stocks->palm oil	−0.0144	0.0446	−0.3220	−0.0529	0.0505	−1.0462	−0.1029	0.0575	−1.7884	−0.0598	0.0237	−2.5258
Panel J: rice sample													
Egypt	Rice->stocks	−0.0815	0.0469	−1.7353	−0.0142	0.0599	−0.2370	0.0370	0.0431	0.8593	−0.0964	0.0213	−4.5308
Egypt	Stocks->rice	0.0545	0.0480	1.1354	0.0363	0.0618	0.5870	−0.0291	0.0584	−0.4983	−0.0967	0.0220	−4.3866
Nigeria	Rice->stocks	−0.0289	0.0478	−0.6043	−0.0408	0.0554	−0.7353	−0.0350	0.0391	−0.8936	−0.0964	0.0214	−4.5140
Nigeria	Stocks->rice	−0.0284	0.0493	−0.5750	−0.1090	0.0579	−1.8833	0.0004	0.0563	0.0074	−0.0969	0.0219	−4.4203
Tanzania	Rice->stocks	−0.0793	0.0458	−1.7335	−0.0031	0.0639	−0.0493	0.0461	0.0435	1.0593	−0.0745	0.0236	−3.1611
Tanzania	Stocks->rice	0.0115	0.0493	0.2327	0.0011	0.0620	0.0170	−0.0976	0.0577	−1.6900	−0.0211	0.0453	−0.4668
Panel K: silver sample													
Namibia	Silver->stocks	−0.0451	0.0395	−1.1417	−0.0323	0.0441	−0.7314	−0.0913	0.0550	−1.6600	−0.0396	0.0318	−1.2436
Namibia	Stocks->silver	−0.0312	0.0434	−0.7190	−0.0464	0.0486	−0.9541	−0.1046	0.0580	−1.8035	−0.0399	0.0454	−0.8787
Zambia	Silver->stocks	−0.0228	0.0402	−0.5674	0.0391	0.0439	0.8900	−0.0666	0.0509	−1.3071	0.0347	0.0324	1.0732
Zambia	Stocks->silver	0.0047	0.0400	0.1165	0.0208	0.0516	0.4032	0.1114	0.0553	2.0144	−0.0657	0.0201	−3.2717
Panel L: soybeans sample													
Ghana	Soybeans->stocks	0.0199	0.0444	0.4476	−0.0607	0.0569	−1.0674	−0.0787	0.0564	−1.3943	−0.0375	0.0405	−0.9261
Ghana	Stocks->soybeans	0.0926	0.0467	1.9830	−0.0602	0.0508	−1.1849	−0.0219	0.0587	−0.3725	−0.0538	0.0334	−1.6069
Malawi	Soybeans->stocks	0.0242	0.0461	0.5242	−0.0914	0.0542	−1.6865	−0.1130	0.0544	−2.0789	−0.0433	0.0379	−1.1421
Malawi	Stocks->soybeans	0.0211	0.0480	0.4387	0.0201	0.0620	0.3244	−0.1447	0.0607	−2.3829	−0.0555	0.0467	−1.1867
Nigeria	Soybeans->stocks	0.0147	0.0432	0.3397	−0.0300	0.0545	−0.5504	−0.0424	0.0572	−0.7410	−0.0378	0.0439	−0.8608
Nigeria	Stocks->soybeans	−0.0244	0.0408	−0.5970	−0.0228	0.0588	−0.3878	0.0021	0.0541	0.0395	−0.0541	0.0349	−1.5494
Uganda	Soybeans->stocks	−0.0113	0.0477	−0.2374	−0.1250	0.0590	−2.1193	0.1195	0.0546	2.1884	−0.0427	0.0417	−1.0241
Uganda	Stocks->soybeans	−0.0171	0.0465	−0.3670	−0.0741	0.0620	−1.1952	−0.0477	0.0565	−0.8438	−0.0547	0.0495	−1.1062
Zambia	Soybeans->stocks	−0.0909	0.0433	−2.0988	−0.1502	0.0587	−2.5605	−0.0856	0.0585	−1.4647	−0.0372	0.0421	−0.8835
Zambia	Stocks->soybeans	−0.0121	0.0455	−0.2654	−0.1275	0.0611	−2.0881	−0.0615	0.0585	−1.0511	−0.0544	0.0355	−1.5321

Notes. β signifies effective transfer entropy estimates, SE is the estimate's standard error, and t-stats are the test statistics.

found to be negative with differing magnitudes and significance. As indicated earlier, we find that the number of negative ETEs increases with increasing timescales or investment horizons. In a similar vein, the number of significant ETEs increased along with the trading horizons. This explains why from the long-term ETEs in Figure 6 the number of significant ETEs is higher than those in Figures 4 and 5 (medium- and long-term horizons, resp.).

4.2. Results Discussion. Findings of the extent to which one variable learns the state of the other through observation are essential to provide additional insights into the intrinsic information dynamics between the studied variables in a single system [28]. Results from such an analysis help to examine market efficiency in terms of asset pricing [11–13]. The findings from the Rényi ETEs suggest bicausal information flows between global commodity and African equity markets' returns. Across both the signal and frequency-domain ETEs, the findings suggest that commodity markets transmit negative ETEs to equities just as most equities transfer negative ETEs to the respective commodities.

The revelation of negative ETEs implies that knowing the history of the corresponding variable brings more uncertainty than when the history of the recipient variable only is known [15]. Impliedly, the receival of negative ETEs by equities markets suggests that returns on investment in African equities markets bear high risk. Therefore, knowing the history of various commodity market returns results in more uncertainty than when an investor sticks to the history of stock market returns in Africa. This means that once the returns from a particular market are highly risky, adding on assets whose returns bear high-risk results in more uncertainty and portfolio risks. Similarly, when there are negative flows from equities' returns to a particular commodity, knowledge about the commodity's returns bears less uncertainty than when the returns from equities are incorporated in terms of asset allocation and policy management.

By taking a distinct focus from the previous studies that only focused on connectedness between either African stocks [61, 62] or commodities [34, 48, 63] or between commodities and African stock markets [29, 46], our study provides fresh evidence about the multiscale information flow between global commodities and African equities markets. Our findings corroborate the existing works that emphasise the essence of dynamic estimators as opposed to static measures in examining the interdependencies between either commodity classes only (see, e.g., [36–40]) or between commodities and other traditional assets (see, e.g., [34, 41, 42]). More importantly, our findings corroborate those of Tiwari et al. [36] who found that the efficiency levels of commodity markets are nonhomogeneous for different commodities.

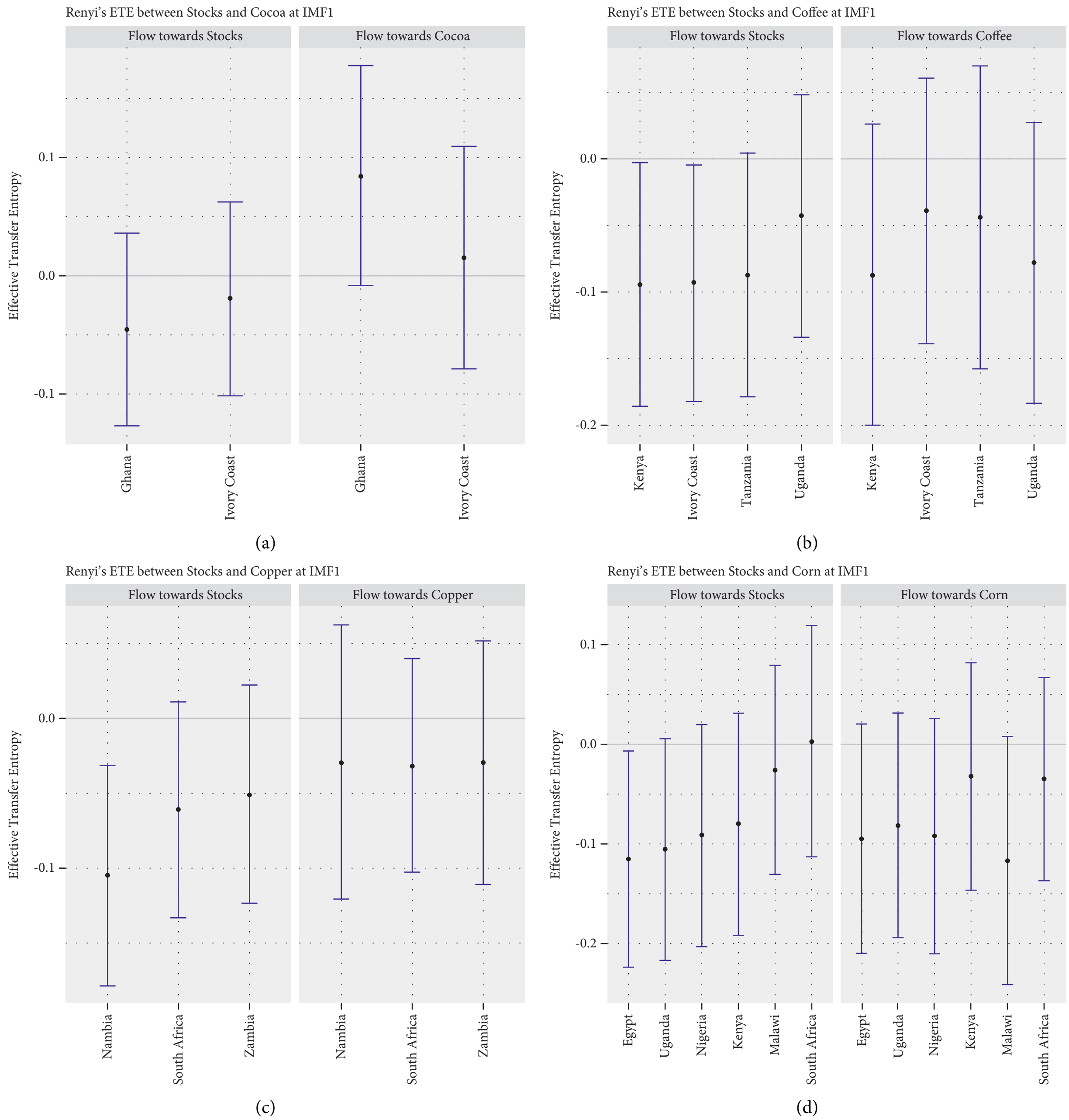
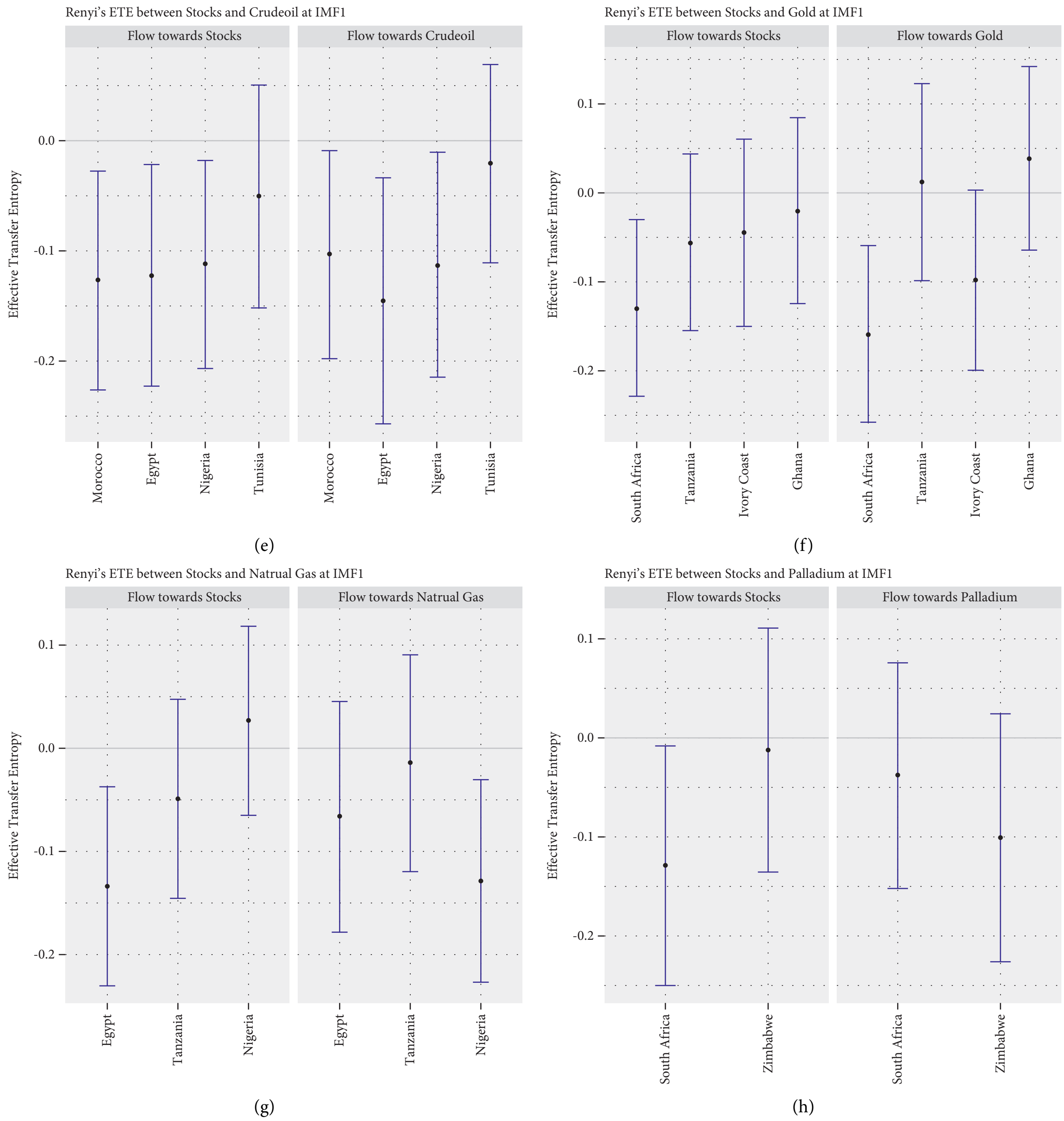


Figure 4: Continued.



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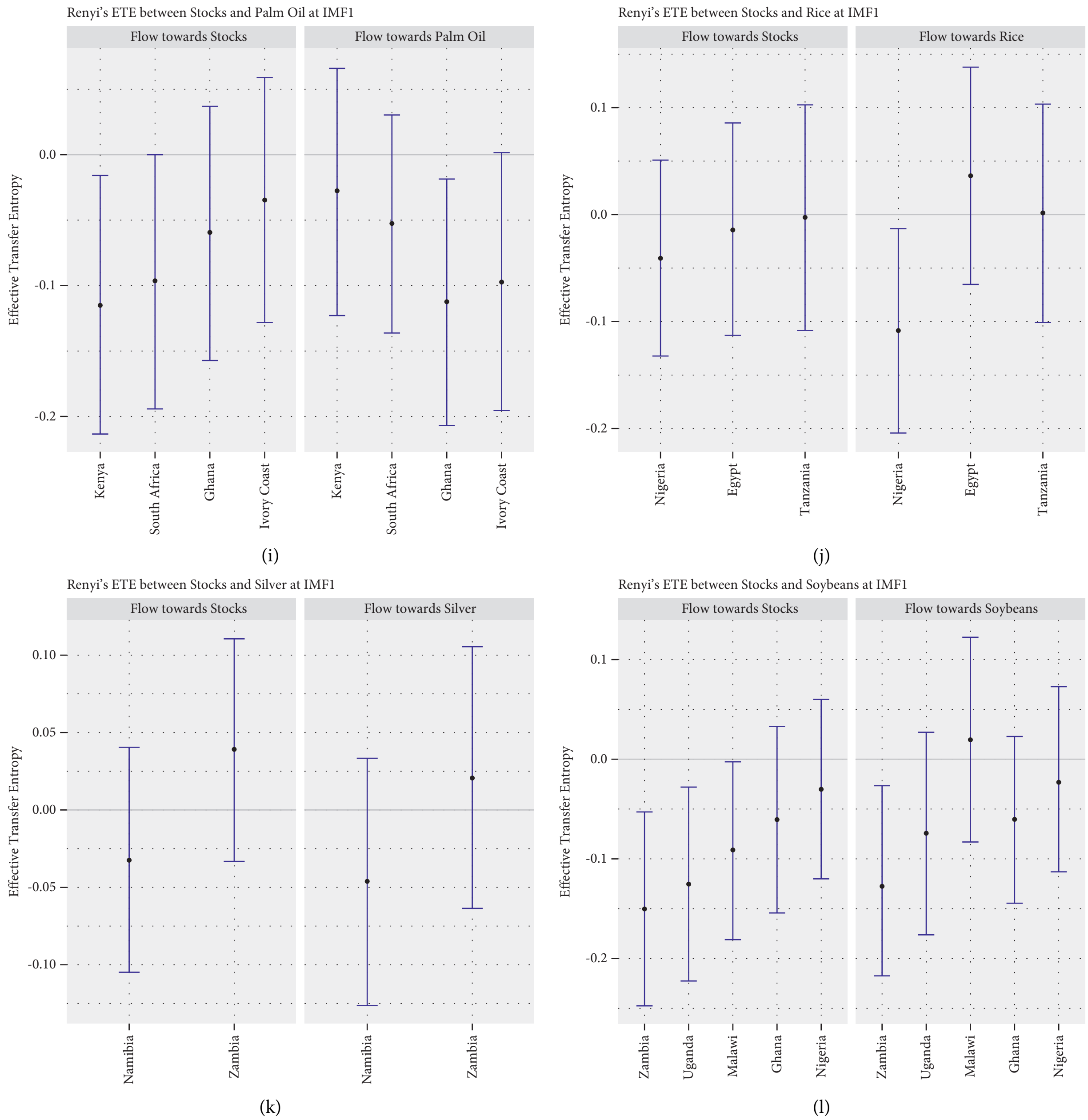


Figure 4: ETEs between stock and commodity markets' returns at IMF_1.

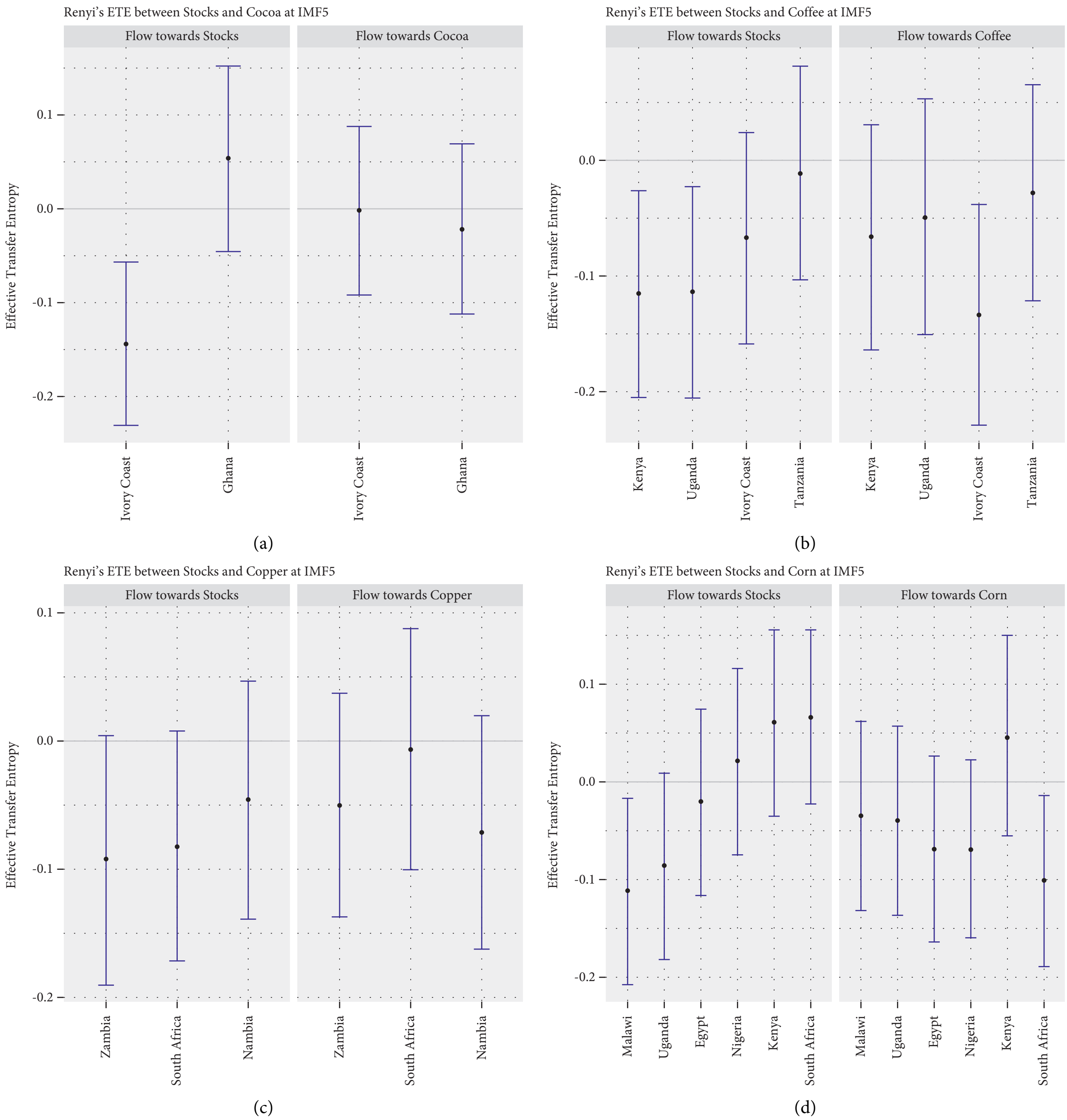
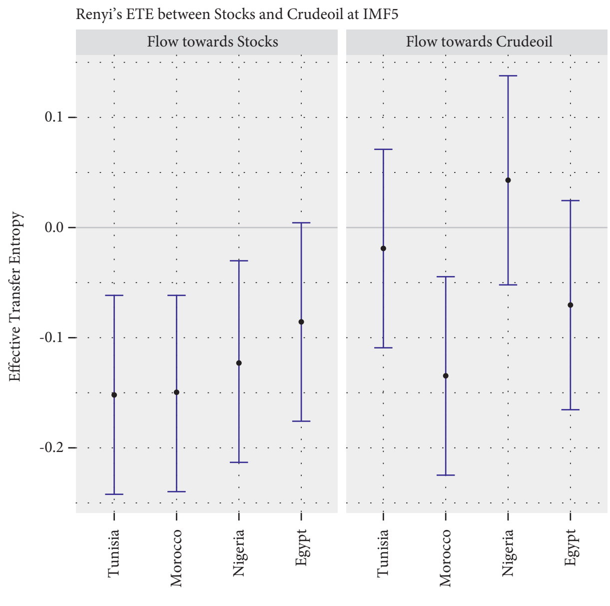
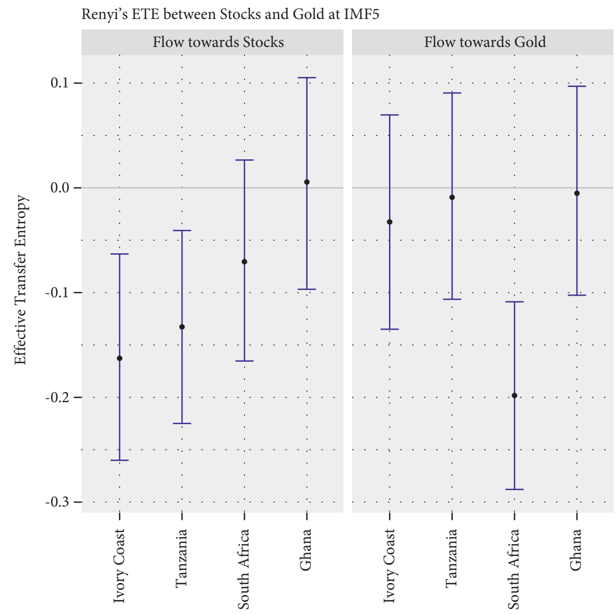


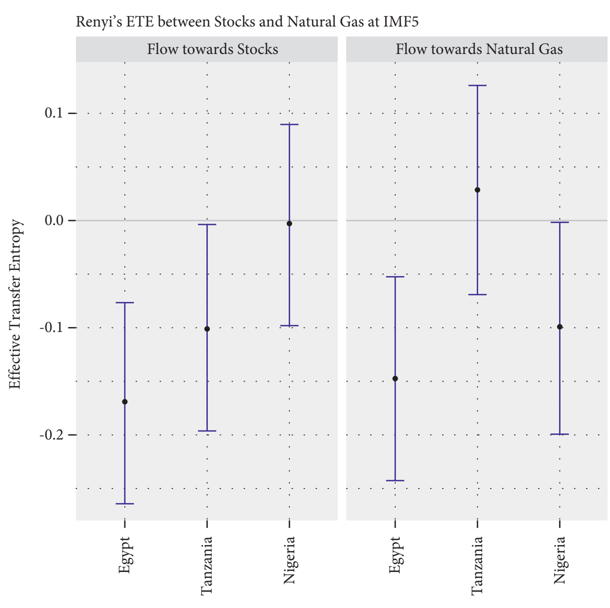
Figure 5: Continued.



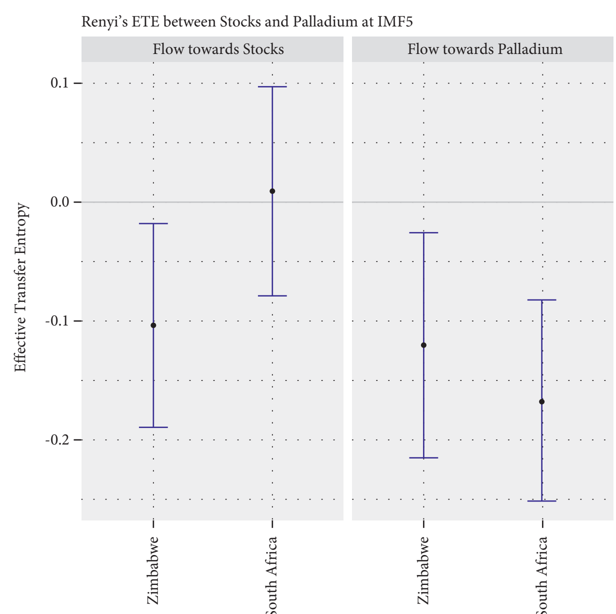
(e)



(f)



(g)



(h)

Figure 5: Continued.

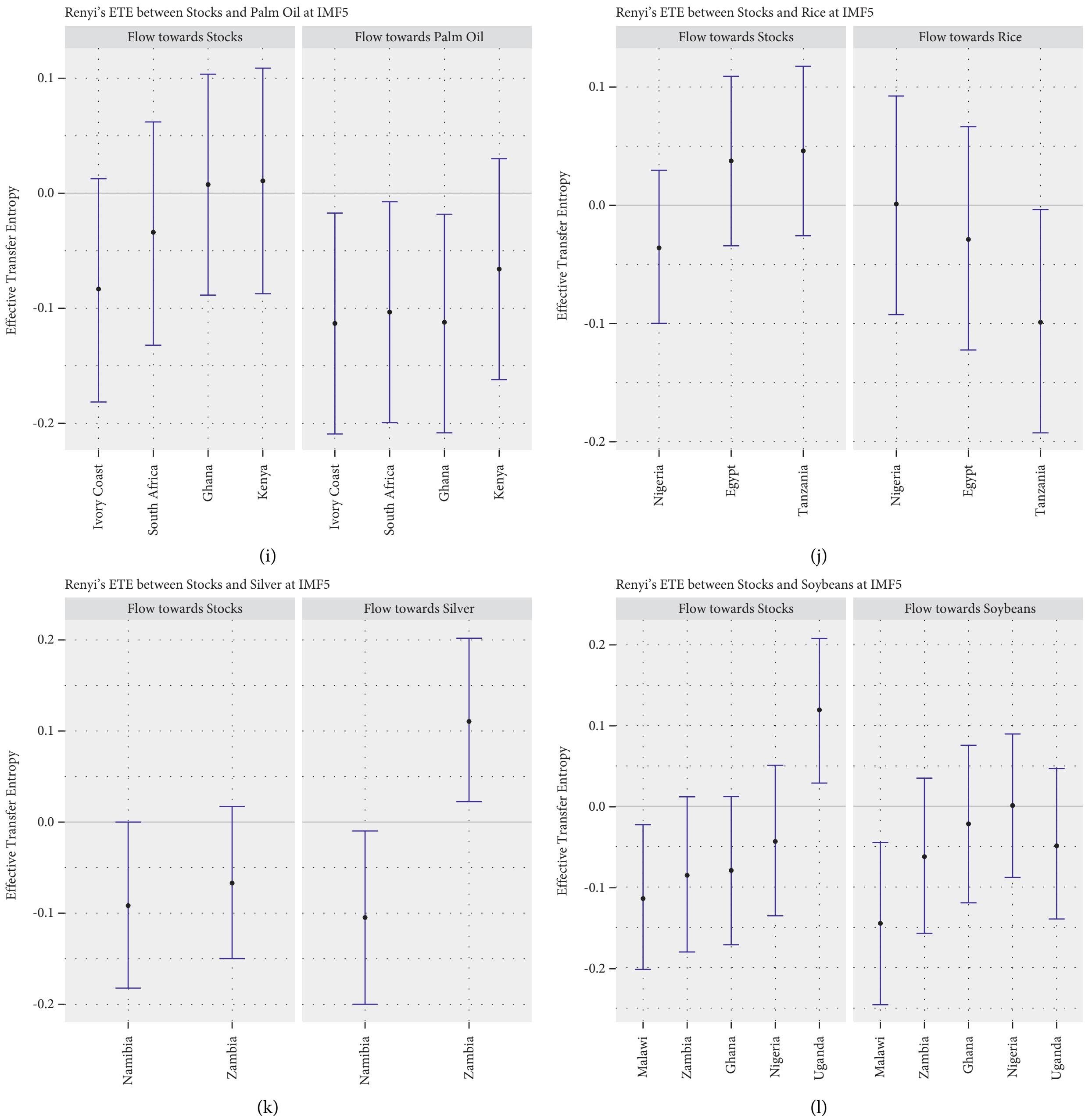


Figure 5: ETEs between stock and commodity markets' returns at IMF_5.

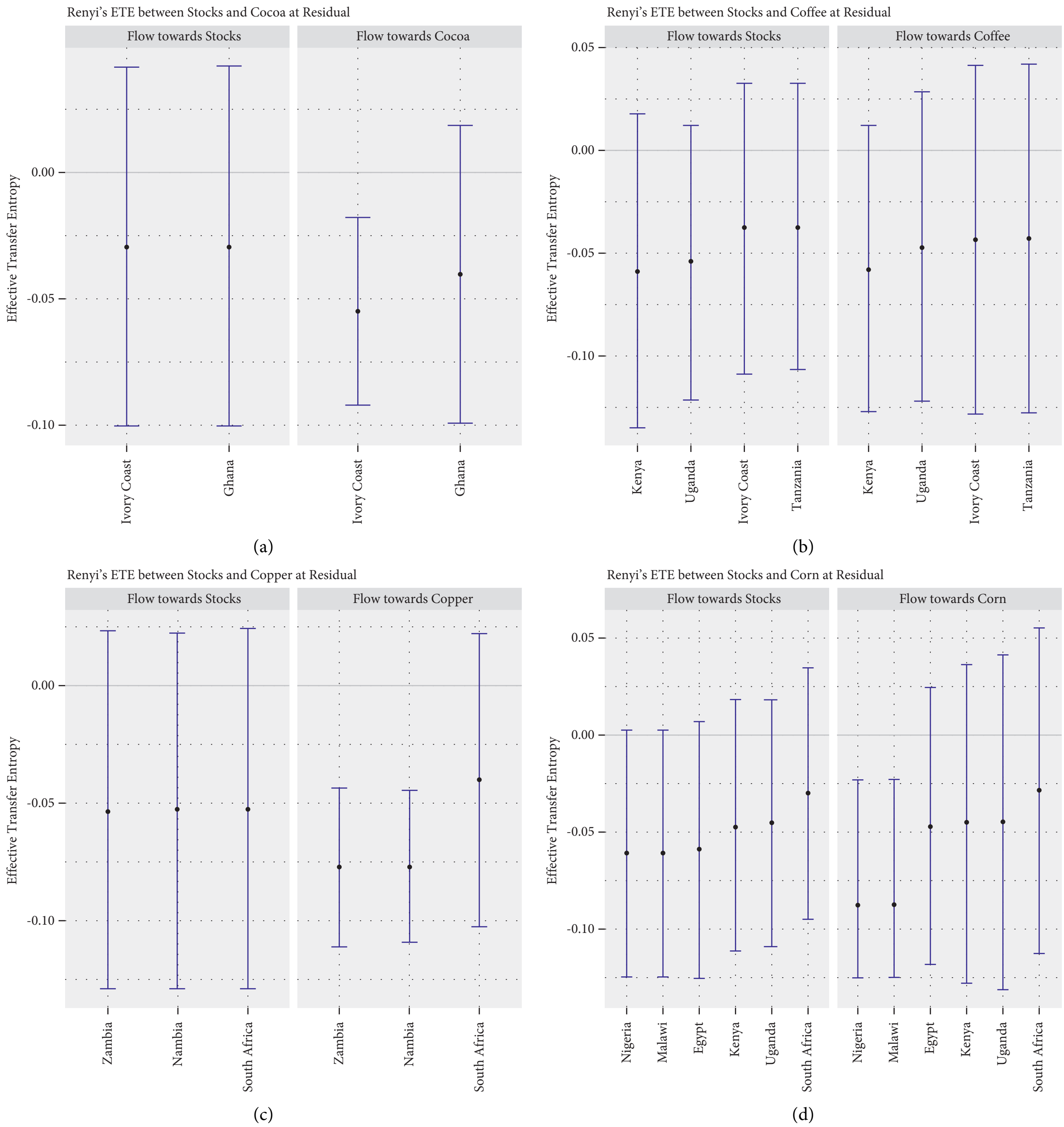
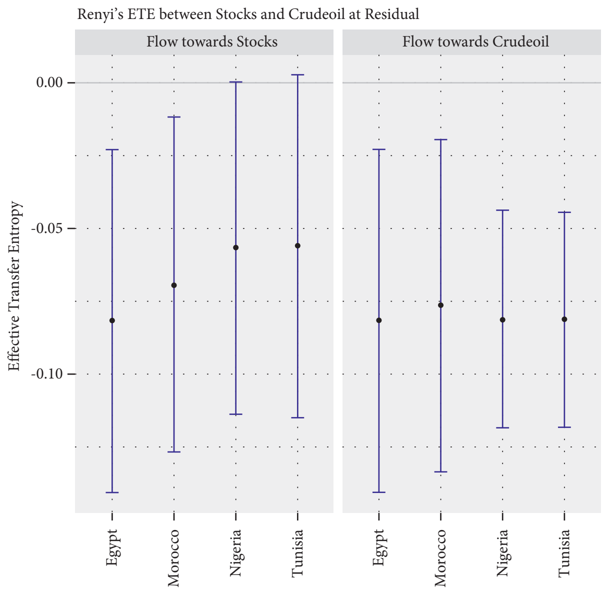
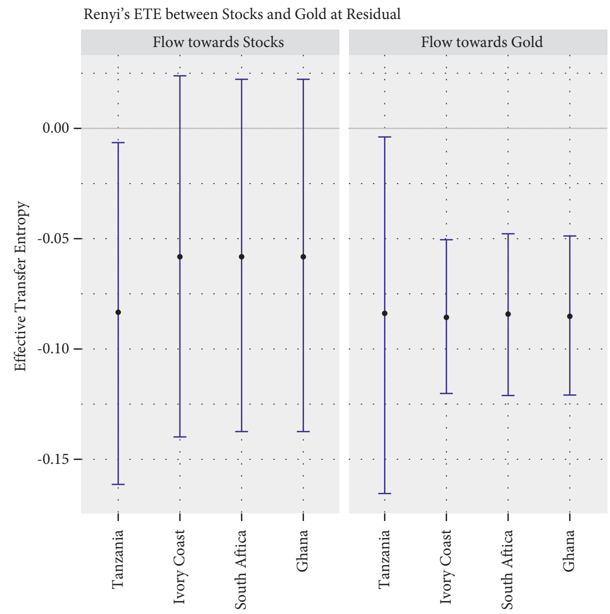


Figure 6: Continued.



(e)



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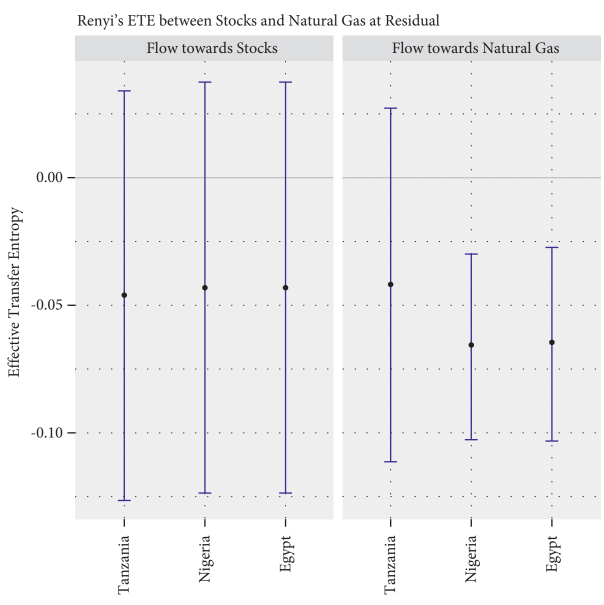

(g)

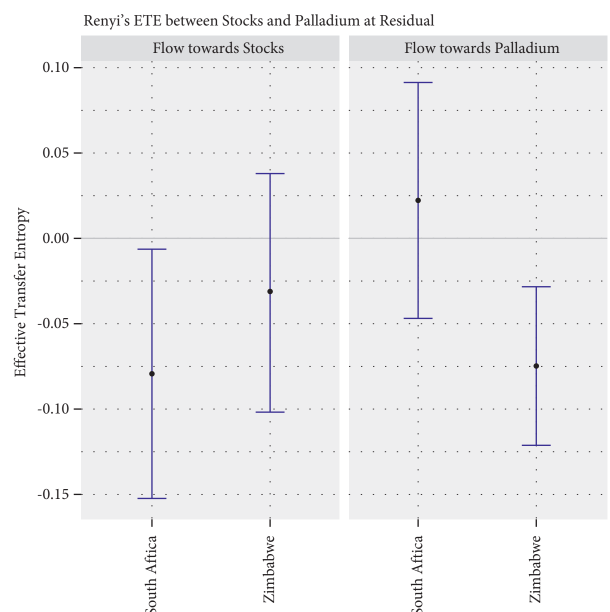

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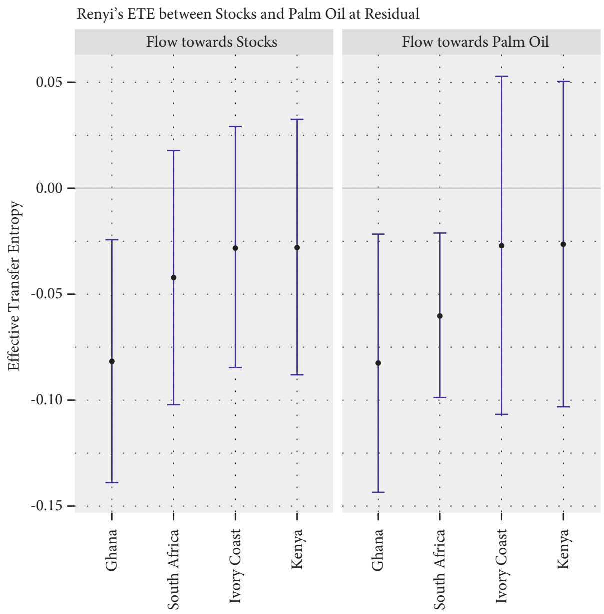
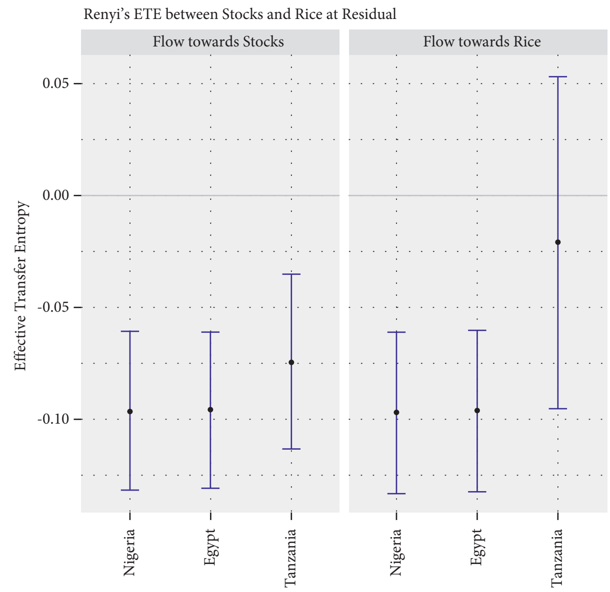
Figure 6: Continued.



(i)



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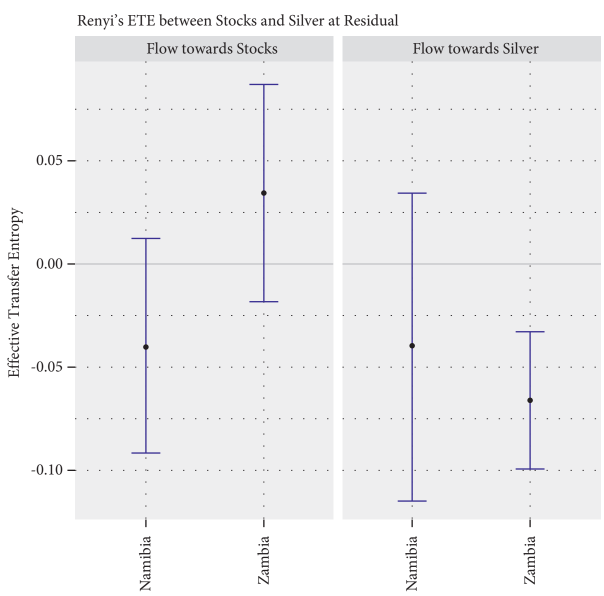
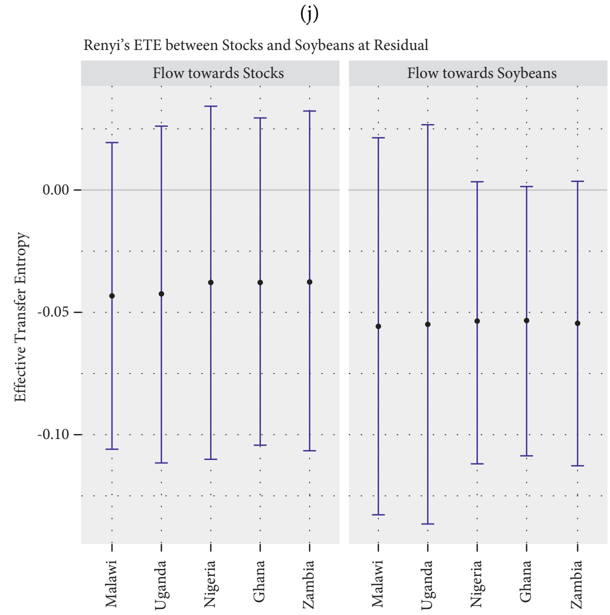


(k)



(l)

Figure 6: ETEs between stock and commodity markets' returns at residual IMF.

5. Implications of Results

Through the transfer entropy analysis, this research revealed that trade between African equities and global commodities results in more uncertainties across investment timescales. Although the implications of this finding do not differ across timescales, the significance is strengthened in the long term, as provided by the residual ETEs, which depict the underlying behaviour of global commodity and African equity markets' returns. Thus, the number of negative and significant ETEs is found to be more at lower frequencies, which represent the long term. Additional implications could be drawn from the perspective of market efficiency as follows.

Fama et al. [11] contend that distressed economic conditions impact asset prices via the flow of information to investors, which then influences investor behaviour. Thus, for markets to be efficient, it is expected that the extent to which a variable learns the behaviour of the other through observation is similar among all variables in a given system [28]. Impliedly, a group of stock markets should have a similar response to the flow of information from a given commodity. The results from this research suggest that the quantification of information flow between commodities and equities' returns yields differing magnitudes, directions, and significance. The implication is that the efficiency levels of various commodity and equities markets are quantitatively dissimilar or nonhomogeneous across commodity types. Hence, these markets are nonefficient based on the mutual information they share.

Whilst these results are contrary to the EMH [11–13], they corroborate the alternative hypothesis to market efficiency (AHME) [64]. The AHME is a more simplistic hypothesis that suggests that rational and irrational investor attitudes are dependent on states of nature and individual investors. It is worth noting that the negative ETEs found in the long term rather lend support to the long-run market efficiency of Fama [13]. Virtually all the ETEs in the long term are negative with most ETEs proving significant. This communicates the principle that, in the long term, when all markets are saturated with available information, the situated information flow between commodities and equities results in comparable magnitudes, direction, and, to a large extent, significance [1, 2, 16, 65]; hence, no undue advantage could be envisaged from the trade between global commodities and African equities.

Investors who are interested in short- and medium-term gains could compete for similar African equities based on the type of commodity they hold in their portfolios. In doing so, market participants should be wary of the tendency of high cross-market linkages between African equities either amid crisis periods or in the long term. This is explained by the competitive markets hypothesis [2], such that the quest for safe assets may lead to increased multiasset connectedness during stressed market conditions. In such periods, high connectivity would annul any diversification benefits in the short- and medium-term periods. In their quest to attract capital flows, African policymakers should incorporate the efficiency levels of their stock markets as well as global commodities when devising policy actions.

6. Conclusions

The study examined information transfer between global commodity and African equity markets' returns with daily datasets spanning from 22 February 2010 to 4 February 2022. Specifically, we tested the efficiency of global commodity and African equity markets' returns in a novel Econophysics approach of a decomposition-based (ICEEMDAN) transfer entropy paradigm. By taking a unique path, we contribute to the strands of literature that examine cross-market linkages. Our specific contribution rests with the literature that examines the connectedness between global commodities and African equity markets by incorporating market efficiency analysis among African equities and global commodities.

In our multiscale analysis, we found significant effective transfer entropies (ETEs) across the short-, medium-, and long-term horizons. Indicatively, the significance of ETEs was mostly found in the frequency domain, which substantiated the need to examine the efficiency of commodity and equity markets across economic trading horizons rather than in a static paradigm (i.e., the signal or at the composite level only). The findings suggest that investing in a single commodity market results in more uncertainty when an investor accounts for the return pattern of African equities. Similarly, investing in any single African equity results in high return uncertainties.

The studied commodity and equity markets negatively observe each other through the mutual intrinsic information they share. With more significant negative transfer entropies, for any given commodity sample, investment in one equity market results in additional uncertainties—in terms of asset returns—when investments are held in their accompanying equities or commodities since they all receive negative ETEs. We conclude that, in the long term, based on the mutual information shared by commodity and equity markets, for any investment in either equity or commodity, adding on similar equities or commodities from the same unified system increases the risk associated with market returns. Our findings divulged that information transfer between commodity and equity markets' returns is bidirectional across diverse frequencies.

In the context of market efficiency, the nature of information transfer between the studied global commodity and African equity markets implies that there are little or negligible chances for any equity-commodity combination to reduce risk or uncertainty associated with market returns. However, with notable variations in the significance of ETEs across the short- and medium-term frequencies, we explicate that the studied commodity and African equity markets are significantly efficient in the situated information flow between them. Specifically, we underscore the operability of the alternative hypothesis to market efficiency and the competitive markets hypothesis in the short- and medium-term horizons, whereas the efficient market hypothesis and the long-term market efficiency operate in the long-term economic trading horizon.

The intrinsic information content possessed by markets serves as a guide to predicting the efficiency levels of markets. Through information transfer, short-term traders could monitor the loopholes in the market efficiency levels between global commodities and African equities to take advantage of arbitrage when needed. Long-term investors like institutional investors are assured of efficient market dynamics between global commodity markets and African equities. Therefore, investments in global commodities and African stocks could be monitored on their information content to predict market performance across trading horizons. Given the uncertainty in returns based on information content, investors are urged to explore other assets that bear low uncertainties with global commodity and African stock markets' returns.

Hinged on our findings, future works could ascertain the efficiency levels of the studied markets across different market conditions using quantile-based techniques (see, e.g., [1, 52, 66]). Additionally, the risk levels of the studied markets could be forecasted to meet the proactive needs of market players. For this purpose, elicitable models (see, e.g., [67, 68]) could be employed. To supplement the findings under an entropy paradigm, future works could examine this issue by employing the reverse dispersion entropy (see, [69, 70]).

Data Availability

All data used to support the findings of the study can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no financial or nonfinancial conflicts of interest.

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